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Acknowledgement

This thesis documents the research undertaken at the University of Stavanger during the spring semester of 2023, and represents the culmination of my two-year master's degree program in industrial economics. As a petroleum engineer with more than ten years of experience at ScanWell Technology, the chosen topic of this thesis directly relates to my background and working experience. ScanWell Technology is an international service company that provides solutions for well integrity and gaslift surveillance to the oil and gas sector. Through this thesis, I was able to leverage my operational experience and academic methods to explore the creation of value within a decision analysis framework, both analytically and strategically.

Despite carrying out this research while working full-time, I am grateful to my colleagues for their support during this busy period, which allowed me to achieve my goal. Additionally, I would like to express my gratitude to the University for enabling students like me to complete our studies, especially given the challenging working conditions during the COVID-19 pandemic.

I would like to extend a special acknowledgement to Rachelle Christine Cornwall, whose dedication was instrumental in driving the field trial that forms the cornerstone of this work. It was an honor to work with such a competent and visionary person, who consistently strived to deliver value-creating changes in her organization.

Finally, I would like to acknowledge the unwavering support of my family during this period. Thank you all for your contributions and encouragement throughout this journey.

Abstract

Decisions in the oil and gas industry determine the direction and course of millions of actions every year. Informally, decision-making can be defined as choosing the alternative that best fits a set of goals. Simple as it is, in the context of oil and gas operations, this statement requires complex analysis and structural methods to comply with. Good decision-making is a skill which, like any other skill, can be improved by learning and practice.

This thesis aims to explore the framework of the decision-making process related to production optimization on aging gas-lifted brownfields. As these fields have reached the end of their primary recovery phase, decisions are required to implement efficient strategies to further optimize their operations. One of the challenges is the lack of quality subsurface and production data that can improve the decision-making process. In addition, different operational and organizational realities make the decision-making and implementation of those complex and demanding.

Decisions with respect to production optimization are heavily dependent on company goals, financial and operational strategies, and facility constraints. This thesis will apply a multi-objective decision analysis theory to this decision-making process, and will provide a framework, trying to help engineers to navigate through this inherent multi-layer analytical and organizational structure.

The key contribution of this study is to provide a basic understanding of the possibilities and limitations of utilizing different gaslift surveillance techniques. Additionally, the study will provide a decision-oriented methodology for implementing gaslift surveillance practices. Finally, the goal of this research is to provide a framework to inform process to any decision related to operation of oil and gas fields considering multiple objectives and stakeholders.

Contents

1. Introduction

1.1 Background

Brown field is defined as a mature field with extensive well coverage and production history. Those fields are typically characterized by older well completion, lack of reliable instrumentation, and reduced well surveillance capabilities. The production from these fields decreases over time due to the depletion of the reservoir pressure. This further leads to a decline in the overall productivity of the field.

The introduction of lift gas to a non-producing or low producing well is a common method of enhancing production on aging fields. Natural gas is injected at high pressure from the casing into the well-bore and mixes with the produced fluids from the reservoir. The continuous mixing process lowers the effective density and therefore the hydrostatic pressure of the fluid column, leading to a lower flowing bottom-hole pressure. The increased pressure differential induced across the sand face assists in flowing the produced fluid to the surface. The method is easy to install, economically viable, robust, and effective over a large range of conditions, but does assume a steady supply of lift gas.

The steady supply of lift gas requires compression and treatment facilities. Those impose a limitation on the overall lift gas available for allocation. The demand for continuous lift gas will often increase with time as the field matures even more, and water fraction in the produced fluids increases. Upgrade of compression and treatment facilities is typically one of the alternatives for production enhancement from the field.

Engineers working with optimization of the gas-lifted wells rely primarily on wireline interventions to obtain the core fundamental data required to make informed optimization decisions. Wireline gradient surveys provide quality data for optimization work. On the other hand, the frequency of measurements is often limited and cannot satisfy effective optimization. Wireline and slickline services are typically involved in multiple operations across the field and can cause operational bottlenecks. Prioritizing utilization of wireline resources is a demanding task. Utilizing wireline operations for gathering downhole data for optimization is often postponed due to unexpected events requiring intervention. Inherent operational risk associated with well intervention can result in downtime and increased number of HSE nonconformities.

Intervention-less techniques such as tracer-based surveillance and acoustic measurements have been discussed in the industry for 30 years. Nevertheless, implementation of those as a primary method for gaslift surveillance is rare. General skepticism for accuracy of the measurements often prevents engineers from evaluating possible trade-offs for this uncertainty. Reduced operational risk, increased amount of valuable data, operational scalability and reduced environmental and logistical footprint may be valuable for operations outperforming the consequences of reduced accuracy. In addition, the accuracy of intervention-less measurements should be better quantified for direct comparison to the traditional method.

This thesis aims to compare intervention-less techniques for gaslift surveillance to conventional flowing and static gradient surveys performed by wireline and slickline. To investigate the deliverables and the accuracy of the measurements. Further, to apply multi-objective decision analysis (MODA) theory on a decision for implementing one or the other practice across the field. This type of decision typically sweeps across multiple organizational, strategical, and financial objectives and goals which contributes to the complexity of navigation through this decision-making process.

The thesis will provide a decision-oriented methodology for implementing gaslift surveillance practices. Although the work is focused on gaslift surveillance, the value creation and decision-making philosophy and methodology used is applicable for any operation related decision on oil or gas field.

1.2 Key contribution

The first key contribution of this work is to provide basic understanding of possibilities and limitations for ad-hoc surveillance activities on aging gas-lifted brownfields. To map the deliverables and the expected accuracy of so-called intervention-based and intervention-less gaslift surveillance technics.

Moreover, to develop a decision analysis tool that can help engineers to improve multi-objective decision-making. To present a case-study of a decision made by an oil and gas operator in the middle east region for transition to intervention-less surveillance of its gas lifted assets.

Finally, to present a framework that can be applied for any decision with multiple objectives considering trade-offs on a common scale. This framework should ultimately result in a high-quality decision-making process, improving decision quality and achieving better outcomes.

1.3 Procedures and tools

This work considers two significant aspects related to the operation of oil and gas fields – gas lifted operation of aging brownfields and multi-objective decision analysis.

The work drafts multi-objective decision analysis theory and applies this framework on a decision related to gaslift surveillance services. A significant part of the workload was to analyze the deliverables of typical alternatives in this field and to understand the value-drivers behind this decision-making process.

Several advanced software tools were used during this work, including ScanWell's in-house build software for tracer and acoustic well surveillance and Palisade @Risk for sensitivity analysis of the constructed decision model. No technical description of those tools is provided, rather the analysis and output will be presented.

Basic knowledge of gas lifted operation is helpful, but no specific prerequisites or software knowledge is required to understand this thesis.

The decision analysis presented was based on data collected during field trial referenced multiple places throughout the work, nevertheless the framework allows engineers to model their own preferences with only use of Excel.

1.4 Multi-objective decision analysis role in the O&G industry

Multi-objective analysis is an important tool for identifying optimal solutions. In a complex and dynamic environment like the oil and gas industry, this process is improving decision-making and increasing the probability of desired outcomes.

This framework helps decision-makers to understand trade-offs and identify the most suitable solution that meets the various objectives. The process involves the use of mathematical models and optimization techniques to generate multiple scenarios and evaluate their performance against the objectives.

Although engineers spend most of their time on analytical challenges related to their field, structuring decision-analysis process prior addressing the outcomes is less common practice. Improving the decision-making process will improve value and outcomes from millions of decisions taken by engineers every year.

1.5 Structure

The reader of this thesis assumed to have similar knowledge of gas lifted operation as the author. Some basic knowledge in probability theory and statistics is required to follow a similar framework for any decision. In case of lack of description of certain matters, I would encourage the reader to study additional sources of information.

The thesis is divided into 6 main chapters. Besides introduction, discussion of the results and conclusion which presented in chapters 1,5 and 6 respectively – the chapters describe decision analysis theory (chapter 2), basic principles of gaslift surveillance on aging brownfields (chapter 3) and presents a decision model constructed in chapter 4 based on theory presented in previous chapters.

1.6 Abbreviations

BHFP/BHFT – Bottom Hole Flowing Pressure / Bottom Hole Flowing Temperature

CDF – Cumulative Distribution Function

EOR – Enhanced Oil Recovery

EoS – Equation of State

FGS/SGS – Flowing Gradient Survey / Static Gradient Survey

GLIR – Gas Lift Injection Rate

GLR– Gas Liquid Ratio

GOR – Gas Oil Ratio

HSE – Health Safety Environment

IP – Intellectual Property

KPI – Key Performance Indicators

MASP/ MOP – Maximum Allowable Pressure / Maximum Operational Pressure

MODA – Multi-objective decision analysis

MPFM – Multi-Phase Flow Meter

NPT – Non-Productive Time

NPV – Net Present Value

OPEX/CAPEX – Operational Expenditure / Capital Expanditure

P/T – Pressure / Temperature

SCP – Sustained Casing Pressure

SPM – Side Pocket Mandrel

VLP/IPR/GLPC – Vertical Lift Performance / Inflow Performance Relation / Gas Lift Performance Curve

WHP/WHT – Well Head Pressure / Well Head Temperature

WITSS – Well Intervention-less Tracer Surveillance Survey

1.7 Reference documents

The thesis has been using available published resources on the subject matter. The list of references included in bibliography. The methodology proposed is to a large degree based on a framework from a book by Clinton W. Brownley – Multi objective decision analysis. Managing trade-offs and uncertainties. This book is the main reference for the decision analysis drafted and the case study presented in this work. It is recommended to revert to this book if the thesis does not sufficiently elaborate on certain terms and concepts.

Some information that is presented in this work is taken from internal documents by ScanWell Technology. These documents are not publicly available, but I encourage the reader to contact the company if further information on this matter is required.

2. Theory

2.1 Decision analysis theory

The modern business environment presents a multitude of complexities and uncertainties that make decision-making a challenging task. Factors such as balancing multiple objectives, accommodating varying stakeholder risk attitudes, identifying suitable alternatives, evaluating intangible factors, and predicting future consequences with precision, contribute to this challenge. Despite the desire for a simpler environment, it is acknowledged that the inherent nature of business operations ensures that this complexity cannot be avoided.

This structure of the business environment poses significant difficulties in making informed and defensible decisions. In the current high-stakes business scenario, decision-makers must be able to justify their choices to a range of stakeholders. Given the inadequacy of informal analysis in addressing most critical business decisions, it is imperative for professionals to adopt a systematic approach and have access to a set of tools that aid in decision-making and provide the necessary support for justifying their decisions.

To evaluate a decision-making process, one should start by defining what constitutes a decision. A decision could be defined in multiple ways. First, as an opportunity to make a choice between at least two different things (Hastie, 2001). Alternatively, a decision can be defined as an irrevocable allocation of resources (Howard R. A., 1988). Decisions are typically made by people or groups with authority on behalf of an organization or an enterprise and typically increase in their complexity with the number of stakeholders involved and the clarity of the objectives. The discipline of decision analysis has been supporting decision-makers to evaluate the decision-making process.

Professor Ronald Howard of Stanford university in his first publication defined decision analysis as a body of knowledge and professional practice for the logical illumination of decision problems (Howard R. A., 1966). Since then, decision analysis became a multidisciplinary science, involving mathematics, psychology, management science, and modern decision theory. It inherits learnings from traditional areas such as – economics, business, finance, probability and statistics, computer science, engineering, and psychology (Paul Newendorp, 2000)

2.2 Decision quality

First, we need to understand how to evaluate decision quality. A positive outcome would be the natural way to evaluate a decision. But decisions and outcomes are different in nature. The distinction between decisions and outcomes exists due to the unpredictability surrounding every choice. In a world of certainty, this differentiation would not be necessary. Despite the uncertainty, one can still make a wise decision but still end up with an unfavorable result.

Assuming that good decisions will more likely generate positive outcomes, then the best way to increase positive outcomes, which get us more of what we truly want, is to make good decisions and execute them well. (Meyer, Spetzler, & Winter, 2016, p. 7)

To judge the quality of a decision before we act, we need to understand what goes into it. Jennifer Meyer, Carl Spetzler, and Hannah Winter in their book Decision Quality suggest that every decision can be dissected into six distinct elements, each of which must be addressed with quality (Meyer, Spetzler, & Winter, 2016, pp. 12-17). This leads to six requirements for a good decision:

1. Appropriate frame
2. Creative alternatives
3. Relevant and reliable information
4. Clear values and tradeoffs
5. Sound reasoning
6. Commitment to action

The frame outlines the challenge or opportunity being addressed, including the decision to be made. The decision basis comprises of three crucial elements that need to be clarified: alternatives define the available options, information represents our knowledge and beliefs, and values reflect our desired outcomes and aspirations. These three elements are combined through reasoning, which leads us to the optimal decision based on our values and knowledge. Reasoning provides clarity of intention, but mere intention is not enough. A true decision requires action, so commitment to implement the decision must also be a key component.

The goal of making quality decisions must be understood from the outset. Every decision leads to consequences, or outcomes, which we cannot fully control in an uncertain world. As a result, even a well-made decision may have either a positive or negative outcome. However, by ensuring that our decisions meet the standards of quality, we can be confident at the time of decision-making that we have made a high-quality choice.

2.3 Challenges in making quality decisions

Making significant business decisions can be incredibly difficult, frequently due to the intricacy of the decision itself or the circumstances under which it is being made. Effective decision-making requires bringing together rational decision-makers with high-quality information about alternatives, preferences, and uncertainty. However, the information may not always be of the desired quality and can include erroneous and biased data. The information may be limited to opinions, advice, and conjecture rather than objective observed data. Additionally, the decision-makers may not always be rational due to conflicting goals within the organization and time pressures. Decision analysis plays a crucial role in bridging the gap between decision-makers and the best available information for effective decision-making.

Decision problems are complex, and this complexity can be characterized in three dimensions (Parnell, Bresnick, Tani, & Johnson, 2013, p. 25):

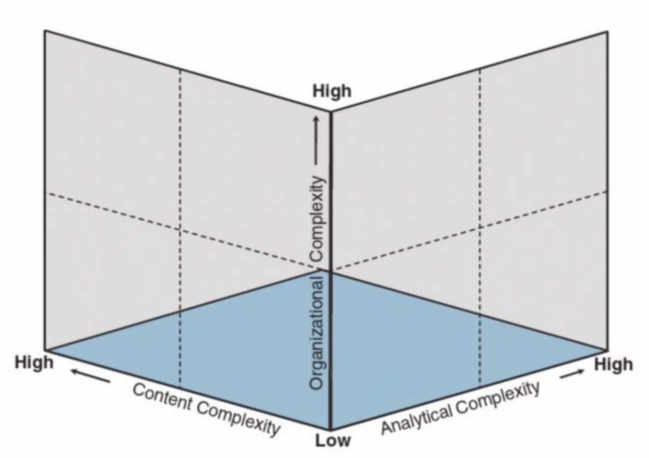


Figure 1. Dimension of decision complexity

Content complexity varies from simple scenarios with limited data and stable decision-making environments to complex scenarios with excessive data and dynamic decision contexts. Analytic complexity can range from straightforward deterministic problems with low uncertainty to complex problems with high uncertainty, multiple alternatives, and a complicated value hierarchy. Organizational complexity can range from a solitary decision-maker with similar stakeholders to multiple decision-makers needing consensus from a diverse group of stakeholders with differing perspectives. It is optimal to address organizational complexity during project setup by engaging the appropriate individuals in the proper manner.

According to Clinton W. Brownley in his book “Multi-Objective Decision Analysis: Managing Trade-Offs and Uncertainty” (Brownly, 2013, pp. 3-6), there are multiple factors that can contribute to the complexity of the decision-making process:

1. Multiple objectives
2. Limited alternatives
3. Intangible goals
4. Long-time horizons
5. Sequential nature of decisions
6. Interdisciplinary substance
7. Uncertainty and risk
8. Attitude toward risk
9. Value trade-offs
10. Multiple decision-makers

2.4 Methodology

The decision analysis process might vary from industry to industry and between different architects. Clinton W. Brownley proposed Multi-Objective Decision Analysis (MODA) as a structured approach to making informed decisions. According to MODA, the decision-maker must choose the most appropriate alternative by assessing two elements: (1) the probability of the potential outcomes for each option, and (2) the decision-maker's personal preferences for the potential outcomes associated with each option.

One of the distinctive features of this methodology is that it separates the analysis of uncertainty from the analysis of preferences (i.e., values or utilities). Analysis of uncertainty refers to an assessment of the likelihood of the potential consequences, whereas analysis of preferences refers to an assessment of the attractiveness of the potential consequences to the decision maker (Brownly, 2013, p. 7).

The analysis of uncertainty in MODA uses probability theory, subjective probability, and data to determine the likelihood of uncertain outcomes. It is preferable to use subjective terms, as it clarifies and makes the degree of uncertainty explicit and ensures a common understanding. The analysis also offers a more comprehensive approach than relying on simple summary measures.

Preference (i.e., value or utility) analysis relies on a decision maker's unique set of values and preferences to assess how attractive the various consequences or outcomes are to the decision maker. This analysis has two components. The first component consists of specifying a preference ordering over the range of outcomes for a single evaluation criterion. The second component consists of specifying a preference ordering over all of the evaluation measures; that is, making trade-offs among the measures (Brownly, 2013, p. 8).

The MODA process, according to Brownly, consists of 12 steps as illustrated in the flowchart diagram below (Figure 2. Decision-making process (Brownly)).

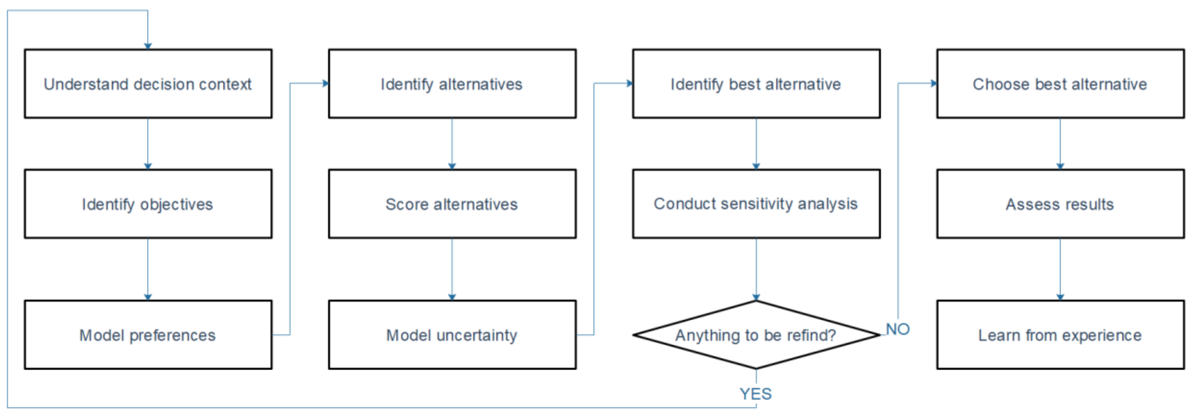


Figure 2. Decision-making process (Brownly)

Alternative step-by-step decision-making process was proposed by Bratvold & Begg (Bratvold & Begg, 2010). Their suggested framework consists of 3 main phases – structural, modeling, and assessing, further broken down into subcategories.

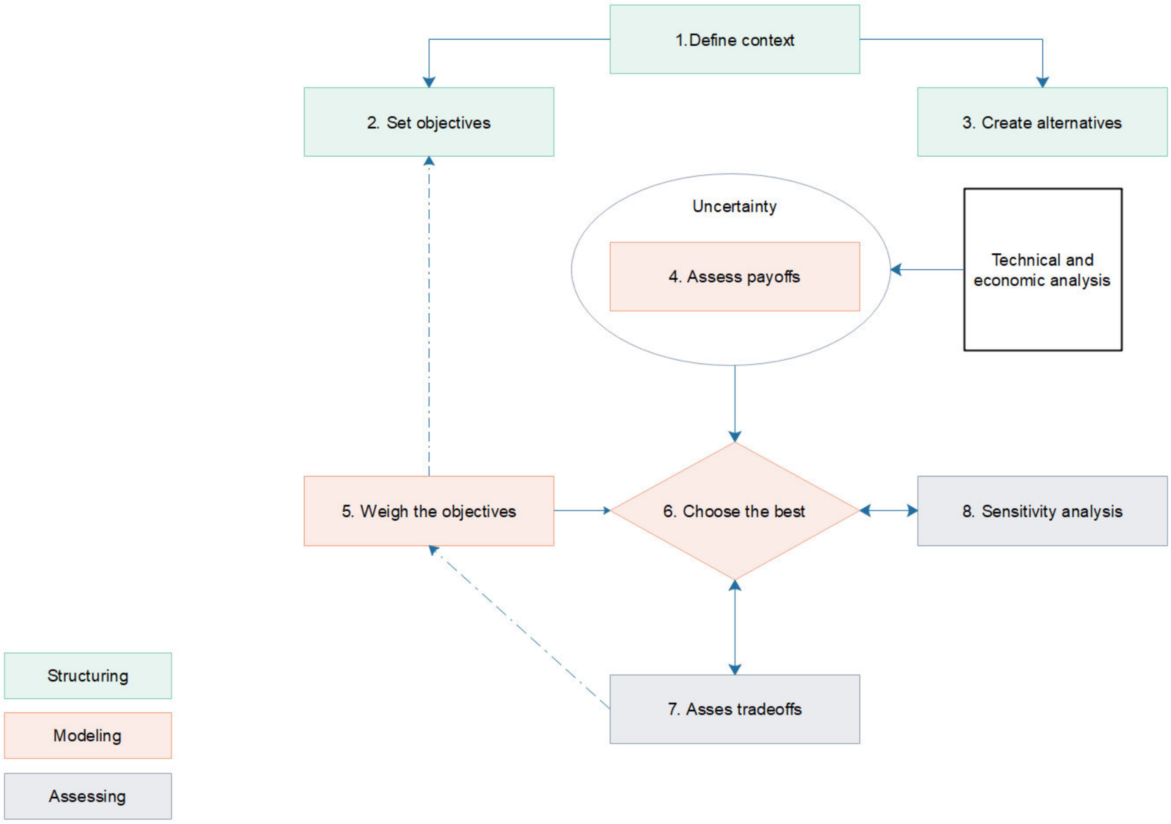


Figure 3. Decision Analysis Process (Bratvold & Begg)

The steps illustrated in Figure 2. Decision-making process and Figure 3. Decision Analysis Process (Bratvold & Begg), visualize a framework for a structural approach to a decision-making process. A structural approach is required for increasing the probability of making good decisions in complex organizational structures - Figure 1. Dimension of decision complexity. Although the steps proposed by Brownly and Bratvold & Begg show some differences, the core principles underlying those structures are critical for the process of making a good decision.

There are several other variations to this methodology in the academic literature that carry some differences in structuring the steps and phases of decision analysis process, but we can observe a similar pattern in the main phases required for executing the process. We can divide the process in three main phases:

1. Understanding or defining the context of the decision and setting the goals for the desired outcome.
2. Creating or identifying alternatives. Modeling uncertainty of consequences and constructing evaluation criteria. Further, evaluating possible trade-offs and choosing the best course of action.
3. Assessing the results and proceeding to implementation.

2.4.1 Context, objectives, and goals

Brainstorming values and objectives is crucial for the decision-making process. Sadly, objectives are frequently not expressed clearly in many situations. Decision makers may not articulate their objectives for a variety of reasons such as their belief in a strong understanding of their goals without explicitly stating them, a feeling of time constraints, or an unfamiliarity with expressing and organizing their objectives. Given that values represent the matters of significance in a decision and objectives provide context and direction to these values, it is imperative to invest time in clearly defining the objectives that will guide the decision-making process.

The objectives hierarchy outlines the reasons for paying attention to the decision. Higher-level objectives are broader and are shaped by the lower-level objectives below them, while lower-level objectives detail important elements of the higher-level objectives above them. Organizing the hierarchy can be approached from the top or the bottom and often involves alternating between both methods. The WITI (Why Is That Important?) test utilizes a similar process by asking questions to establish the arrangement of fundamental objectives within the hierarchy. The top-down method involves starting with a very general, high-level objective and inquiring, "What do you mean by that?" The response to this question assists the decision maker in clarifying the higher-level objective by identifying lower-level objectives that represent the essential aspects of the higher-level objective (Brownly, 2013, p. 27).

2.4.2 Alternatives and evaluation measures

Objectives often are not equal in all aspects to be directly compared to each other. Suitable evaluation measures should be established to be able to evaluate possible trade-offs between the identified alternatives and quantify the extent to which objectives are achieved.

Brownly proposes three types of evaluation measures: natural, constructed, and proxy (Brownly, 2013, p. 30). While evaluation measures do not always fit neatly into one of these categories, the groupings are useful for highlighting the distinctive characteristics of the evaluation measures.

2.4.2.1 Natural evaluation measures

A natural evaluation measure is the logical one. The one that any person with standard competence and knowledge in the subject matter of the decision problem can understand. Typically, this measure can be related to maximizing profits or minimizing costs. Natural measures should be directly quantifiable and comparable.

2.4.2.2 Constructed evaluation measures

In many cases, natural evaluation measures cannot be directly applied to evaluate alternatives as a function of achieving objectives. When the objectives are not directly measurable, a mechanism should be constructed to evaluate and weigh the alternatives. Typically, problems such as improving the company's image, building resilience toward future energy trends, increasing satisfaction and engagement of employees, or increasing competence in a certain field, etc. are difficult to measure or compare. A constructed evaluation should be directly related to the problem and the nature of alternatives. A possible approach here could be breaking down the objective to common outcomes of each alternative and score those accordingly. Measures such as number of applicants for available or new position can help to understand the image of the company, satisfaction survey performed can provide insight on customer satisfaction, internal competency tests can provide information on knowledge and competency changes among the different groups within the company. Constructed measures then scored providing equal basis for evaluation.

One scoring method for constructed measures is creating scale with defined levels. This scale uses two or more levels describing the objectives associated with each level of scale. The set of levels should span the range of objectives, the definition of each level should be unambiguous and the difference between levels should be significant.

Another proposed method for scoring alternatives is the weighted scale. This type of measure would be suitable for alternatives with objectives of a different value. This method requires setting a base line for value and comparing the alternatives relative to this base line. This way components with different values can be weighted on a common scale.

In some cases, constructed measure cannot be applied directly and proxy evaluation may be required. The value of the proxy measure is in its capacity to quantify the associated fundamental objectives indirectly (Brownly, 2013, p. 35).

2.4.3 Desired properties of alternatives and evaluation measures

Alternatives are the means for achieving the main goal for the specific decision. A decision, on the other hand, is the opportunity to choose the best alternative. To choose the better alternative for reaching the desired outcome, one should have number of good alternatives to choose from. A good alternative is one that can potentially lead to desired outcome. Increasing the number of alternatives in the evaluated set, will also improve the chances of a decision makers to achieve their goal.

Developing a set of good alternatives is a challenging task. Creative thinking, experience, market knowledge and correct competence, can all contribute to developing such a set. Brainstorming and idea checklists, value-focused thinking and strategy generation tables are some of the techniques that could be applied in the process.

Another challenge that can arise while working with creating alternatives, is too many options. The number of alternatives suitable for each decision-making process, should be proportional to the nature of the decision. Too many alternatives may require too many resources, too few, may reduce the ability to make a good decision. It is important to apply suitable techniques for reducing the number of alternatives without compromising the desired outcome. Different screening criteria can be applied to reduce the number of alternatives.

The main purpose of evaluation measures is to establish a scoring system for the alternatives and their objectives. Therefore, the chosen measures should be measurable and understandable. This way the available alternatives can be evaluated as a function of their objectives on a common scale. Uncertainty in outcome by choosing one or another alternative will be incorporated in the model and help the decision maker to choose the best option based on the available information.

2.4.4 Developing alternatives under uncertainty

Identifying the alternatives to reach the objectives and goals set at the first stage of the process is the basis for understanding the tangible options setting the complexity level of the decision. Spending time on mapping possible alternatives and their attributes helps to better evaluate different perspectives on possible solutions to the problem. Furthermore, understanding the constraints and predicting possible consequences of each alternative under uncertainty is required to further construct suitable evaluation measures.

One of the major challenges to develop a good set of alternatives is the uncertain outcome of a particular alternative.

In the context of decision analysis, uncertainty and risk are two important concepts that are often used interchangeably but have different meanings.

2.4.4.1 Uncertainty

Uncertainty is a concept that refers to a lack of knowledge or information about the future. In decision analysis, it is often related to outcomes of different alternatives chosen by the decision maker. Uncertainty can be caused by a number of factors, such as incomplete or unreliable data, complexity of a problem, unpredictability of certain outcomes affected by external factors or inherent randomness or variability in the system.

We are willing to accept uncertainty if it is not affecting the outcome of our decisions. On a country, when the decision is highly affected by uncertain factors, we must manage this uncertainty in the decision-making process.

In decision analysis, uncertainty is typically represented using probability theory, which provides a framework for quantifying and managing uncertainty. This involves assigning probabilities to different possible outcomes, based on available information and data, and using these probabilities to evaluate the expected value or utility of different decisions. Engineers are often tasked to reduce the uncertainty to a manageable level and engage in technical analyses and finely tuned predictions to minimize uncertainty. However, uncertainties also provide opportunities and potential upsides that could be exploited.

The concept of probability is familiar to us from everyday conversations. What are the chances for rain or to be stuck in traffic, what is the odds that a team would win or lose a game etc. Intuitively, for repeating events, we assess probabilities as a long-run relative frequencies (Brownly, 2013, p. 74). Alternatively, probability represents a decision-maker degree-of-belief about the likelihood of uncertain event. As a measure of a decision judgment as to the likelihood of an uncertain event, probability is ultimately subjective. In fact, with probability as a subjective concept, people might judge the likelihood of an event differently and so assign different probabilities to the same event. Howard argued that there is no such thing as truly objective probability (Howard R. A., 1966). Probability reflects a person’s knowledge (or equivalently lack of knowledge) about the outcomes of an uncertain event. Probability is a state of mind and not a state of things. It is common to think that probabilities can be found from data, but they cannot. Only a person can assign a probability, considering any data or other knowledge available (Bratvold & Begg, 2010, p. 62).

When considering probability concept as a subjective assessment of a likelihood of different events, the competence, experience, and access to correct information, can significantly affect the ability to assign the correct probability to different outcomes. Dedicated methodology improves this assessment and guards against challenges within personal judgment of different decision makers.

2.4.4.2 Expected value

The concept of expected value is a useful concept in decision analysis theory. It provides a way to summarize the behavior of an uncertain variable in a single number. The expected value of an uncertain event is the weighted average of the possible outcomes (X) where the weights correspond to the probability of the possible outcome (P): $E(X) = \sum P\ (X = x)$.

Expected value can be used as a criterion for alternatives with unknown outcomes. The expected value provides a way to assess the potential outcomes of a random process, and can be used to make decisions based on probabilities and potential payoffs.

2.4.4.3 Risk

Risk refers to the likelihood or probability of a negative outcome or event occurring. It is the potential harm or loss that could result from a particular decision or action. Risk can be quantified and measured, and it can be managed through various strategies, such as risk avoidance, risk mitigation, risk transfer, or risk acceptance.

2.4.4.4 Uncertainty and risk role in decision-making

Uncertainty and risk are factors that must be evaluated during the decision-making process. The presence of uncertainty and risk make the decision more challenging and complex, as it involves managing factors that can significantly impact the decision and its outcome.

Uncertainty can lead to ambiguity, confusion, and indecisiveness, making it challenging to select the best course of action. However, uncertainty can also provide opportunities and potential upsides that can be exploited to create value and gain a competitive advantage (Bratvold & Begg, 2010).

Risk involves weighing the potential benefits against the potential costs or negative consequences of the decision. Risk management strategies are used to minimize the negative impacts of risk and ensure that the decision achieves the desired outcomes.

3. Gaslift operation on aging oil fields

3.1 Background

Oil producing formation will decrease in pressure with time. Several techniques can be applied to keep producing reservoirs with depleted pressure. This includes supporting pressure in the formation by EOR techniques and improving the vertical performance of the wells by artificial lift. Continuous gaslift is one of the most common types of artificial lift among gas lifted fields around the globe.

Aging fields converting to gaslift after up to several decades of natural production will typically meet multiple challenges with respect to surveillance of the producing wells. Well surveillance is required to make informed decisions to optimize production and manage well integrity in gaslift operation. Lift gas allocation and integrity of downhole completion are topics of major significance, which have been broadly discussed in the industry.

Traditional methods for gaslift surveillance and diagnostics on aging brownfields rely on wireline services, a method with growing constraints to adapt to constantly evolving well and operational challenges (Cornwall, Shkorin, Guzman, & El-Majzoub, 2021).

The means for gaslift surveillance of aging wells are often limited. Over-engineering during initial design of instrumentation, metering and control equipment presents a challenge to the ability to accurately meter and control the allocation of injected gas for artificial lift.

Lack of measurements of bottom-hole flowing pressure together with lack of information regarding down-hole lift gas distribution, prevents from identifying the optimization opportunities in time.

As a field matures, the greater demand for lift gas in conjunction with limitations imposed by existing facilities and prevailing operating conditions (compression capacity, lift gas availability, well shut-in for workover, etc.) can prevent optimal production from being achieved.

The integrity of the downhole completion also plays a critical role in the efficiency and safety of gas-lifted operation. Downtime due to work-over, well-interventions or other maintenance and troubleshooting activities contribute to reduced production from the assets.

3.2 Basic principles of gaslift operation

A successful operation of a gaslift system is contingent upon a variety of interconnected components, including subsurface equipment, flow lines, separation and storage equipment, compressors, GLVs, and surface controls. These components function within a closed system that requires a high-pressure source of gas. The efficiency of the gaslift system is reliant upon the careful design and implementation of all these elements.

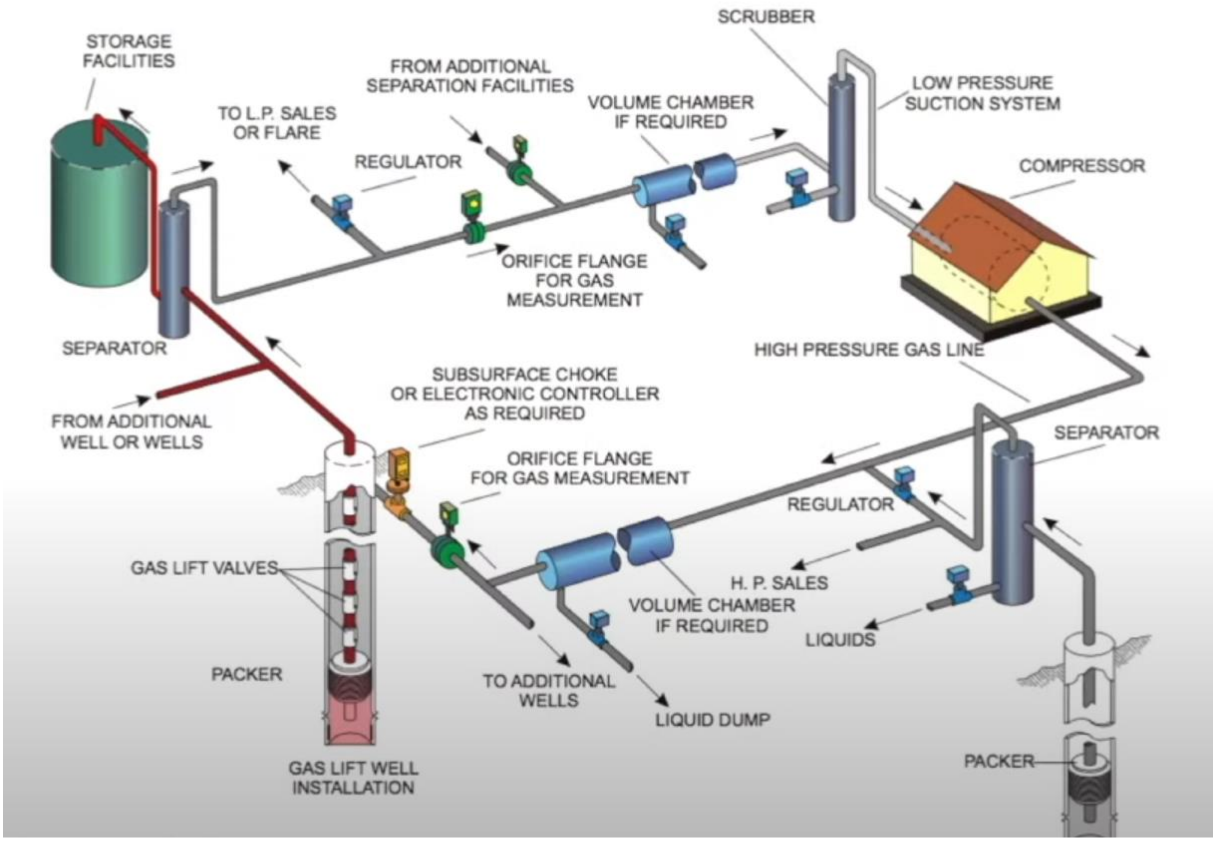


Figure 4. Gas Lift System

3.2.1 Surface gaslift facilities

The lift gas is compressed prior to injection using a compressor facility. The capacity of compressor has its limitation, hence functions as a boundary for total lift gas allocated between the wells.

Produced natural gas is typically the source of gas supplied to the compressors. Treatment of the produced gas may be required to ensure safe and reliable compression process. Surface facilities such as drying and scrubbing processes of the produced gas require maintenance and optimization and can also affect the overall gaslift capacity or create bottlenecks for the operation.

3.2.2 The wells

In terms of their structure, gas lifted wells are similar to naturally producing wells. The side pocket mandrels (SPMs) of gas lifted wells are equipped with gas lift valves. To initiate the gas lift process, pressurized lift gas is injected into the production annulus at the wellhead and travels downwards towards the operating gaslift valve. The operating gaslift valve injects the lift gas into the tubing through a nozzle/orifice, and mixes with the produced fluids. This mixing results in reduced density, hence less heavy fluid than the original hydrocarbon mix.

This property change allows the system to overcome the pressure drop in the production tubing while being lifted to the surface.

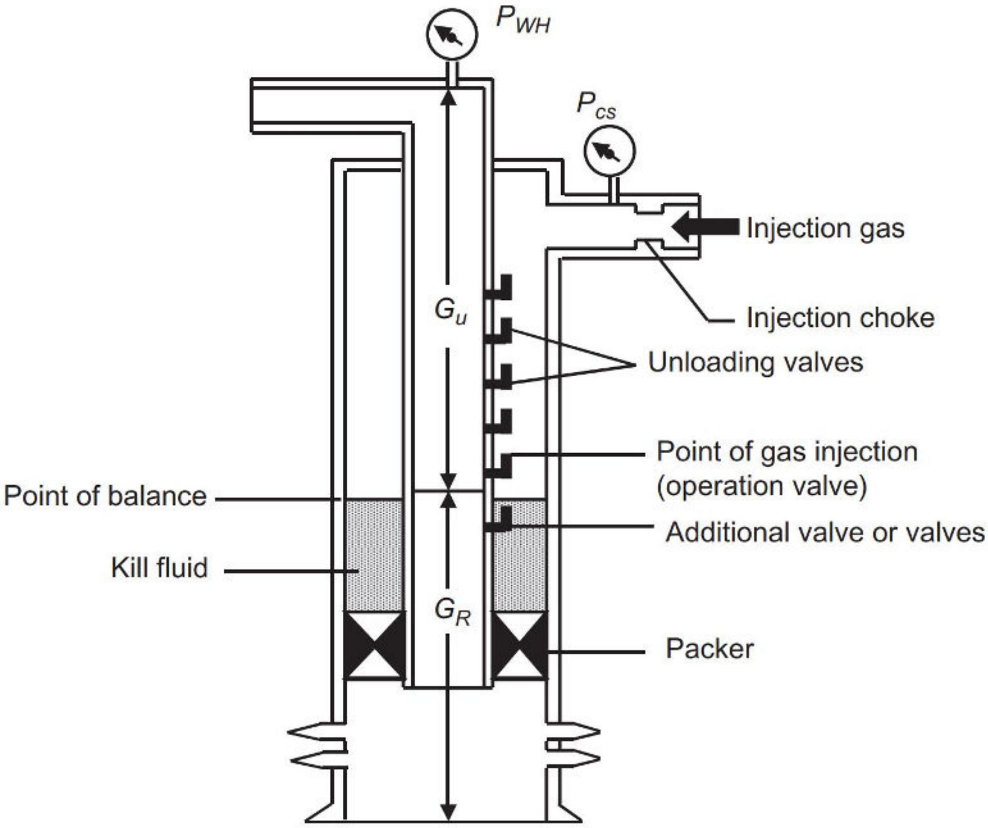


Figure 5. Gas lifted well

3.2.3 Production well-test facilities

Production well-test facilities such as test separators and in line MPFMs are required to quantify the production rates for each phase from single well. Test headers are typically an integrated part of larger production facilities where the wells can be diverted separately from comingled production and tested. Where those facilities are not available on site, the service can be outsourced to a 3rd party service company that will perform the required testing with temporary equipment.

The production data is further used to evaluate well performance – to map optimization opportunities with respect to inflow performance and vertical lift. Data as flow rates and fluid properties for each phase can be recorded during well test with suitable instrumentation and planning.

Although well test facilities are commonly available on oil producing assets, it is a typical bottleneck component of production process on larger facilities with many wells. Frequent testing is required to be able to make sure production is in its optimum state, while in addition to production testing, test separators are used in other applications where particular wells must be separated from the comingled production. For instance, flow-backs and clean-ups after acid stimulation and squeezes, isolating sour wells for treatment, testing of chemicals for improving separation and flow assurance, etc.

Those operational realities result in increased maintenance requirement and reduced capacity. Production engineers rarely get access to sufficient amount of test data to address all lifting issues and optimization opportunities in time.

3.3 Gaslift surveillance

To ensure continuous effective gaslift operation the industry is endorsing a proactive approach. Preventive maintenance recently became an integrated part of standard practices in the oil fields. Planned preventive maintenance activities allow efficient allocation of the required resources, minimizing the operational bottlenecks, and securing sufficient budgets for all activities. Troubleshooting and repairs on the other hand, can be optimized with the help of gathered data during preventive work.

All the components of gas lifted operation require competence and attention to avoid sudden failures and shutdowns. The focus in this thesis is on the surveillance of well deliverability to assure maximum production gain and minimum downtime.

The main objective of deliverability surveillance is to assure optimized production and minimized downtime under the operational constraints.

Production optimization is typically done by constructing a gaslift model for each well using one of the commercial software tools available on the market. Inflow Performance Relation (IPR) and Vertical Lift Performance (VLP) curves are constructed using empirical equations and well deliverability is simulated. Further input such as production well test data, gaslift injection rates and downhole gaslift distribution are used to calibrate those models and identify optimization opportunities. An additional approach for evaluating well performance is to measure or model well's production as a function of gaslift injection rate (GLIR). This relation referred to as gaslift performance curve (GLPC) and allows to evaluate each well in its current state and optimize gaslift allocation across the field.

Minimizing downtime is achieved by optimizing operations requiring production shut-in and reducing activities with increased operational risk that can result in unexpected shutdowns.

The optimization opportunities derived from empirical simulations underly complex operational reality. Limited surveillance data with poor quality, undetected integrity issues such as tubing and casing leaks, result in sub-optimal utilization of identified opportunities (Cornwall, Shkorin, Guzman, & El-Majzoub, 2021).

Maintenance activities on aging wells require frequent interventions. Downhole barrier testing and repair, GLV change, and downhole logging can result in significant downtime and reduce overall production.

3.3.1 Well performance

In order to make educated decisions for effective surveillance of well performance, one needs to understand the theory behind basic production principles, such as reservoir deliverability, inflow performance, vertical lift and gaslift performance curves.

Reservoir deliverability is the production rate achievable from each well at given bottom-hole pressure and it depends on several factors including the following:

- Reservoir pressure (p_e)
- Pay zone thickness (h)
- Reservoir boundary type and distance (r_e)
- Wellbore radius (r_w)
- Reservoir fluid (oil) properties (B_o, μ_o)
- Near-wellbore condition (S)
- Relative permeabilities (k)
- Well completion (vertical, horizontal, fracturing, and multilateral wells)

(Guo, Liu, & Tan, 2017, p. 37)

3.3.1.1 Inflow performance relationship (IPR)

The IPR curve is a graphical presentation of the relation between the flowing bottom-hole pressure and liquid production rate. The magnitude of the slope of the IPR curve is called the "productivity index" (PI or J)

$$J = \frac{q}{p_e - p_{wf}}$$

[1]

Well's IPR curves are usually constructed using reservoir inflow models, which can be from either a theoretical or an empirical basis. (Guo, Liu, & Tan, 2017, p. 53)

The productivity index for oil phase steady-state production above bubble point pressure is independent of production rate, hence can be represented as straight line derived from Darcy's equation, considering the pressure at any point in reservoir is constant over time.

$$q = \frac{kh(p_e - \ p_{wf})}{141.2B_o\mu_o(ln\frac{r_e}{r_w} + S)}$$

[2]

In pressures below bubble point region, the solution gas escapes the liquid and changes the flow dynamics. This makes IPR deviate from the linear trend.

There are several empirical equations for modeling IPR of two-phase production. Vogel's equation [3] is widely used in the industry.

$$q = q_{max}\left[1 - 0.2\left(\frac{p_{wf}}{p}\right) - 0.8\left(\frac{p_{wf}}{p}\right)^2\right]$$

[3]

where q_{max} is an empirical constant and its value represents the maximum possible value of well deliverability.

When the reservoir pressure is above the bubble-point pressure and the flowing bottom-hole pressure is below the bubble-point pressure, a generalized IPR model can be formulated. This can be done by combining the straight-line IPR model for single-phase flow with Vogel's IPR model for two-phase flow.

In terms of optimization for single well of the inflow performance, the operational possibilities are limited. Reservoir deliverability declines with time. During transient flow period in single-phase reservoirs, this decline is because the radius of the pressure funnel, over which the pressure drawdown $(p_e - p_{wf})$, increases with time, i.e., the overall pressure gradient in the reservoir drops with time. In two-phase reservoirs, as reservoir pressure depletes, reservoir deliverability drops due to reduced relative permeability to oil and increased oil viscosity. (Guo, Liu, & Tan, 2017, p. 74)

3.3.1.2 Vertical Lift Performance (VLP)

Vertical lift performance analysis involves establishing a relationship between tubular size, wellhead and bottom-hole pressure, fluid properties, and fluid production rate. Further constructing a relation between flow rates and pressures in the wellbore.

The pressure gradient in the wellbore is dependent on hydrostatic head and friction loss and can be written as

$$\frac{dp}{dl} = (\frac{dp}{dl})_{hs} + (\frac{dp}{dl})_{fr}$$

[4]

The hydrostatic component (hs) is controlled by the density of the produced fluids and the friction component (fr) by the fluid properties and the geometry of the pipe. Slip velocities between the phases must be considered in VLP simulations.

In gas lifted wells, the density of produced fluids is a function of gaslift injection rates and downhole lift gas distribution (lifting depth). Increase in gas liquid ratio (GLR) while keeping a constant rate q, reduces the hydrostatic component resulting in the reduced bottomhole pressure to a certain degree. On the other hand, increased GLR increases friction forces and has a counter effect on the bottomhole pressure. When contribution of the friction forces higher than that of hydrostatic forces, the actual bottomhole pressure (Pwf) begins to grow.

3.3.1.3 Operating condition

The operating point which represents the produced rate at given inflow and vertical performance is the intersection of those curves. Changes in inflow performance and vertical lift characteristics will shift the operating point, hence the production rate (Figure 6. Operating point).

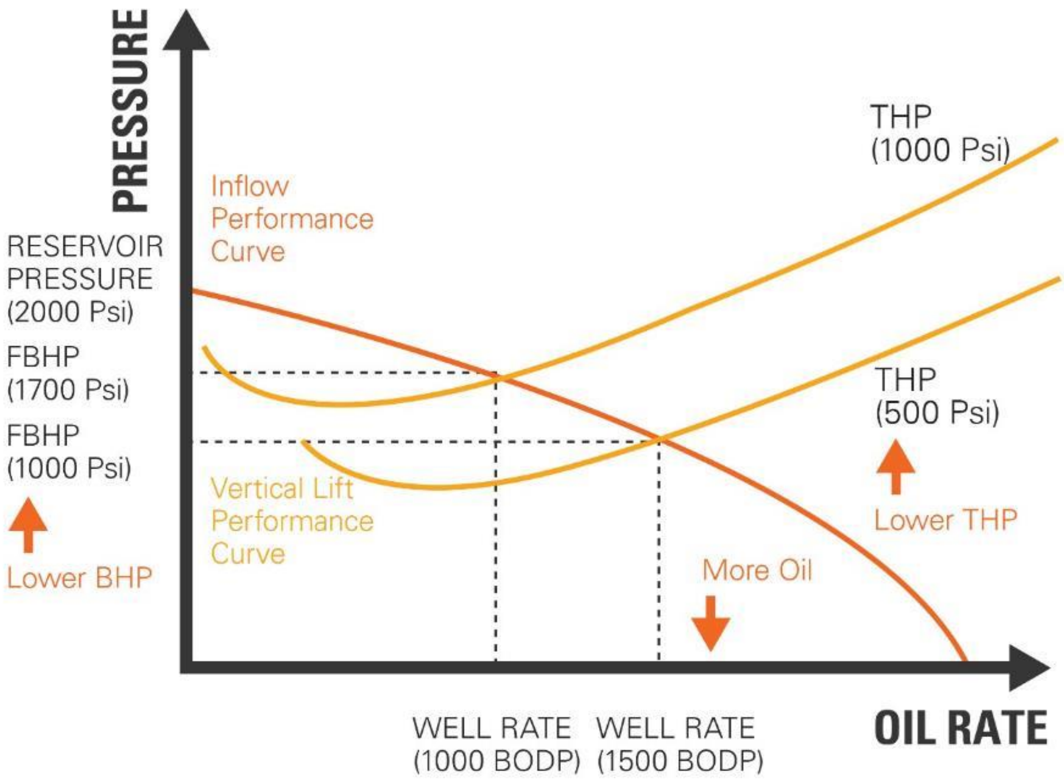


Figure 6. Operating point

3.3.1.4 Gas Lift Performance Curve (GLPC)

Another approach for evaluating well performance is to model wells production as a function of gaslift injection rate. This function is the gaslift performance curve (GLPC) (Mayhill, 1974).

The use of nodal analysis to generate the gaslift performance curve of a single well, based on actual pressure and temperature surveys along with a suitable multiphase flow correlation, is well established in the industry (Rashid, Bailey, & Couet, 2012). The optimum GLIR is often simply set to that furnishing the highest production rate on the gas-lift performance curve (GLPC) (Figure 7. GLPC)

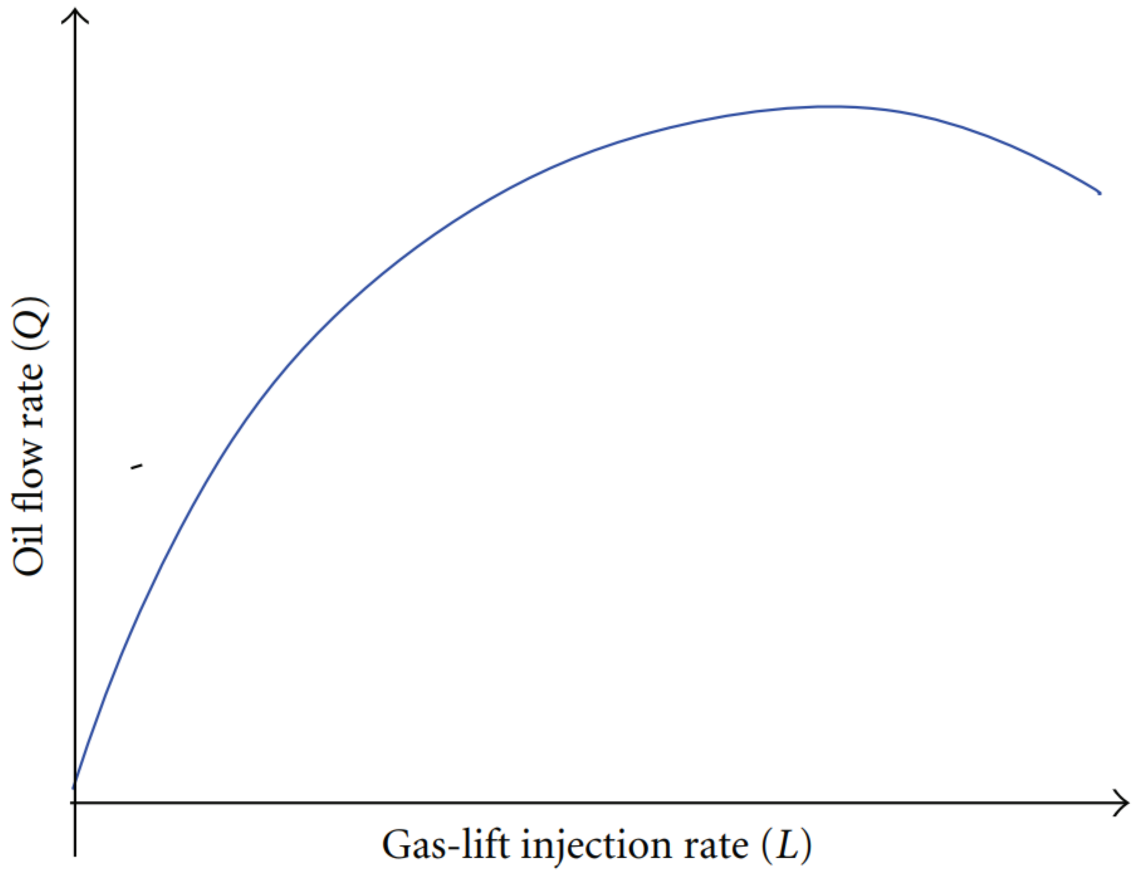


Figure 7. GLPC

To be able to accurately calibrate this function, a multi-rate test is required. Where a well producing with different gaslift rates while production data is recorded under each rate. This data can be further compared with empirical models troubleshooting inflow and vertical lift equations.

The multi-rate test approach allows to understand the liquid production rate as a function of allocated gaslift independently of inflow and vertical lift characteristics. When operational limitations do not allow to optimize inflow or to improve vertical lift, accurate GLPC simulation will provide information regarding optimum GLIR under current well condition, including sub-optimal operating point.

GLPCs are often used to accommodate economic factors by including the net gain (or profit) from oil and gas production, and the costs associated with gas compression, gas injection and water disposal, and so forth. The solution is defined at the point where the incremental profit is zero (see Figure 8. Performance curve representation and solution schemes(d)). Kanu (Kanu, Mach, & Brown, 1981) defined this point as the maximum daily operating cash income (OCI). The optimum injection rate is when the slope of the revenue versus cost curve is one (see Figure 8. Performance curve representation and solution schemes(b)). Kanu et al. (Kanu, Mach, & Brown, 1981) referred to this solution on the GLPC as the economic slope (Figure 8. Performance curve representation and solution schemes(a)) and the equilibrium between revenue and cost as the economic point. Under consistent revenue and cost factors, each of the aforementioned schemes gives rise to the same solution, including profit maximization as a function of gas injection at zero slope (Figure 8. Performance curve representation and solution schemes(c)). The equal-slope concept arises only if the average economic slope is used based on averaged well properties (e.g., an average water fraction over all wells) (Rashid, Bailey, & Couet, 2012).

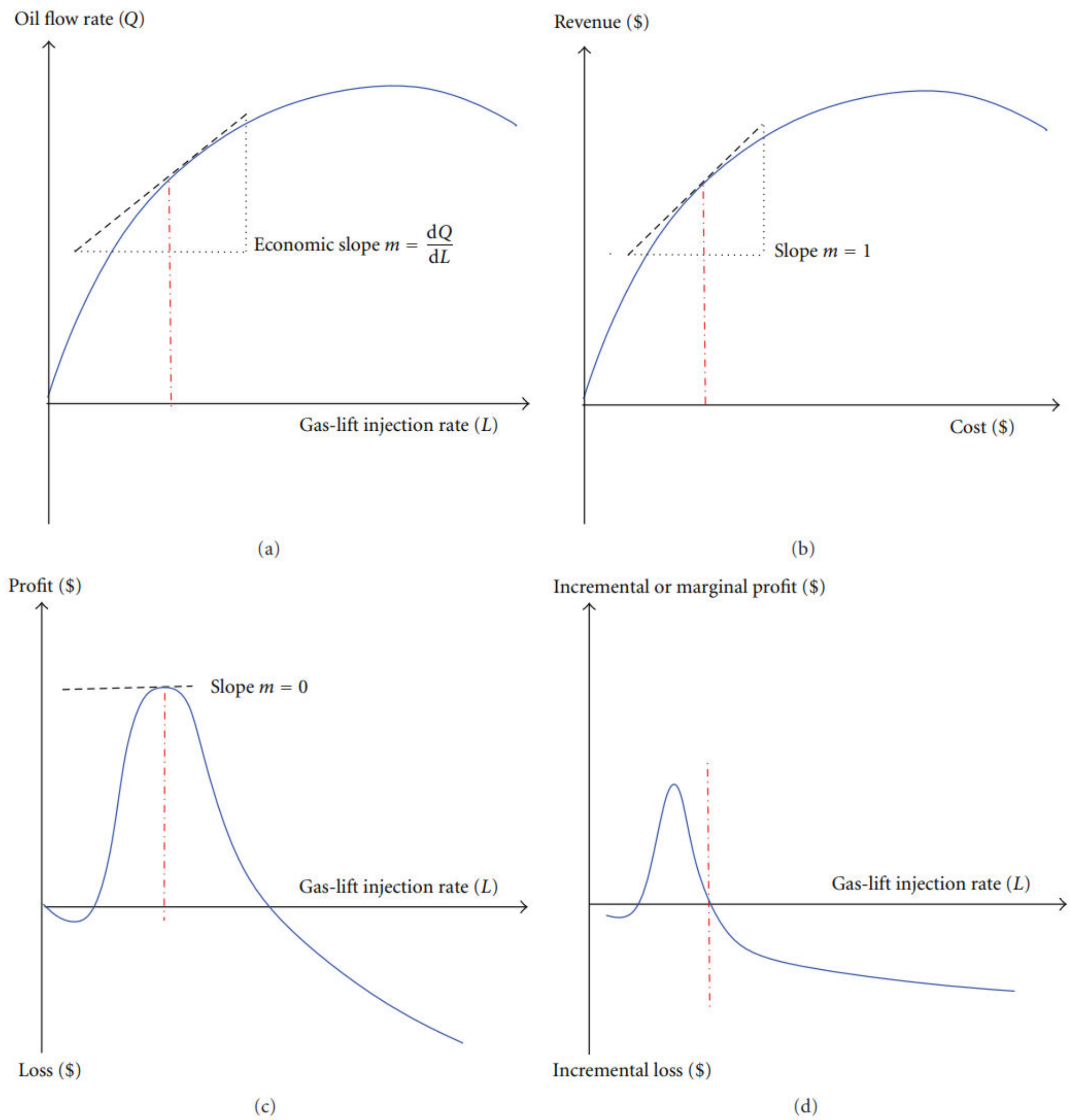


Figure 8. Performance curve representation and solution schemes

In an oilfield, the amount of lift gas available for daily use is often limited by facility conditions and well operations, resulting in variations. Moreover, compressor capacity and separator limits may be influenced by operational conditions and handling facilities during production. Inefficient allocation of lift gas can result in economic losses due to over-constrained or over-designed facilities. Therefore, achieving an optimal lift gas allocation is crucial to maximize oil production or profitability (Rashid, Bailey, & Couet, 2012).

3.4 Conventional methods for gaslift surveillance

Conventional methods for gaslift surveillance traditionally rely on surface and downhole instrumentation, well-test facilities and well intervention operations. On aging fields the available instrumentation is often limited to surface pressure measurements only. Most surveillance activities are executed with intervention-based methods such as wireline and slickline.

Well-testing facilities are also not always available or have limited capacity. This results in operational bottlenecks and limited data from the wells. Third party services can be applied to test the production data from chosen wells and acquire the required data, alternatively, mathematical correlations under uncertainty are used to attempt to match the production models.

3.4.1 Surface and downhole instrumentation

Online and in-line instrumentation is considered the best practice with respect to gathering required data for effective gaslift surveillance. Calibrated and repeatable measurements of pressure and temperature from the wellhead are direct indications of well's production and integrity status. Pressure and temperature trends upstream and downstream the choke, help to spot slugging, changes in phase fractions and control the operation parameters of the well. Pressure and temperature sensors, monitoring the adjacent annuli, allow to spot sustained casing pressure and make sure that wells completion is within MASP and MOP criteria. Downhole pressure and temperature gauges, in both production annulus and tubing, allow to monitor BHFP and BHFT of injected and produced fluids. Flow meter monitoring injected gaslift rate allows to monitor and allocate optimum gaslift volumetric rate to each well.

A well equipped with all of the above, with an established system for logging and processing the data, provides the responsible engineer opportunity and the information required to assess the production and integrity status of the well in real time.

Further, surface, and downhole instrumentation supports most types of well operations. Operations such as acid stimulations, well intervention, inflow testing, coil-tubing operations all can use available surface and downhole data to optimize the execution – reducing operational risk and downtime.

This type of surveillance requires minimum resources, reduced OPEX budget and provides immediate information for quality decisions. When said, this type of surveillance is rarely applicable on aging fields. Limitations with respect to well construction, installation requiring work over, considerable downtime for implementation and significant investments, result in non-viable business case for many operators.

Although standard instrumentation available for well operators today cannot provide all the required information, it is still a very effective approach to gather quantitative surveillance data. Additional measurements, such as fluid composition, downhole leak rates, or any other required parameter, can be collected on an ad-hoc basis using various technics and 3rd party solutions.

3.4.2 Intervention-based methods

Non-conductive wireline has a long history as one of the earliest techniques used for well intervention. Initially, a simple flat steel measuring tape was spooled into wells to obtain basic depth measurements. However, the modern drawn wire slickline, developed in the 1930s by the Otis company (now part of Halliburton), was designed to handle deeper wells. The real breakthrough came with the development of pressure control equipment, which allowed slickline to be deployed with surface pressure, ensuring its widespread adoption.

Over the years, slickline has evolved significantly, with the development of a wide range of downhole tools that enable various interventions. Today, wireline and slickline remains the most widely used method for intervening in live wells due to its cost-effectiveness, shorter operational durations, and availability of transportable equipment. Compared to other intervention methods, slickline generally offers lower costs and higher operational efficiency (Crumpton, 2018, p. 393).

For most aging gas lifted fields, wireline intervention is a common well operation. If a problem can be remedied using wireline, then more complex, costly alternatives such as coil tubing and work-over can be avoided. Common applications for wireline and slickline include:

- Tubing inspections
- Removal of wax and soft scales using broaches and cutters
- Removal of overbalance fluids from a well
- Tubing leak detection
- Running and retrieving downhole flow control equipment such as plugs, chokes, straddles, pack-off, etc
- Installing and replacing retrievable gaslift valves
- Running pressure and temperature gradient surveys
- Repair and replacing of tubing retrievable safety valves
- Fish lost equipment
- Cased hole production logging
- Perforating
- Explosive setting of bridge plugs and straddle equipment
- Casing and tubing caliper surveys
- Downhole camera
- Reservoir monitoring (production logging)
- Condition monitoring (caliper survey and image logging)
- Perforating
- Bridge plug and straddle setting
- Tubing cutting/punching

(Crumpton, 2018, p. 396)

Wireline operations are predominantly conducted on "live" wells, meaning wells that have pressure at the surface and require pressure containment measures. Pressure control equipment is utilized to maintain well pressure while wireline operations are performed, such as running the wireline into and pulling it out of the well. Wireline crews should be highly skilled and knowledgeable about the functioning of this equipment, as well as how to handle unforeseen situations like leaks, equipment failures, and wire breakages. They should be trained to respond promptly and effectively to ensure the safety and success of the wireline operations.

Nearly all wireline interventions are conducted on wells that are equipped with a conventional (vertical) Christmas tree. The pressure control equipment is connected directly to the tree, and the closed tree valves serve as isolation points. At the conclusion of each wireline run, the tree valves are closed, and the lubricator is depressurized. Once the lubricator is fully vented, it can be disconnected and lifted to allow for tool string reconfiguration in preparation for the next run. When the operation is complete, the pressure control equipment is removed, and the tree cap is reinstated. Following verification of the integrity of the tree cap, the well can be restored to production.

Wireline and slickline operations carry inherent operational risk associated with the survey. One of the concerns during any live well intervention is maintaining the pressure integrity of the surface equipment. Different events can occur during execution of a wireline survey. Events such as:

- Leaking Stuffing Box
- Leaking Grease Head
- Broken Wire Strand
- Leaking pressure control equipment: above the blow out preventer
- Leaking Pressure Control Equipment: below the blow out preventer
- Stuck tool string
- Failure of wireline winch power pack or mechanical failure of the winch

Additional challenges arise from exposure to corrosive fluids during interventions. Frequent exposure to corrosive fluids reduces the lifetime of the tools entering the well. This results in increased operational risk and requires increased maintenance.

3.4.2.1 Pressure and temperature gradient survey

Pressure and temperature gradient surveys are the most common conventional method for troubleshooting and surveillance of gas lifted wells.

P/T gradient surveys are commonly run with downhole memory gauges on slickline. By using slickline rather than electric line, the survey can be completed quickly, as there is much less rig-up and rig-down. Because memory gauges do not have a depth measurement in the data, survey points must be taken so that the pressure and temperature data can be calibrated with depth. To achieve this, the survey executed with “gradient stops”, which involves stopping the gauge at a specific depth, while taking note of the depth and time of the gradient stop. This is done at several points in the well and when the data is downloaded after the test, those gradient stops will be identified.

Once the survey points have been collected and analyzed, these points can be placed on a graph of depth vs. pressure/temperature (Figure 9. Flowing gradient survey – FGS).

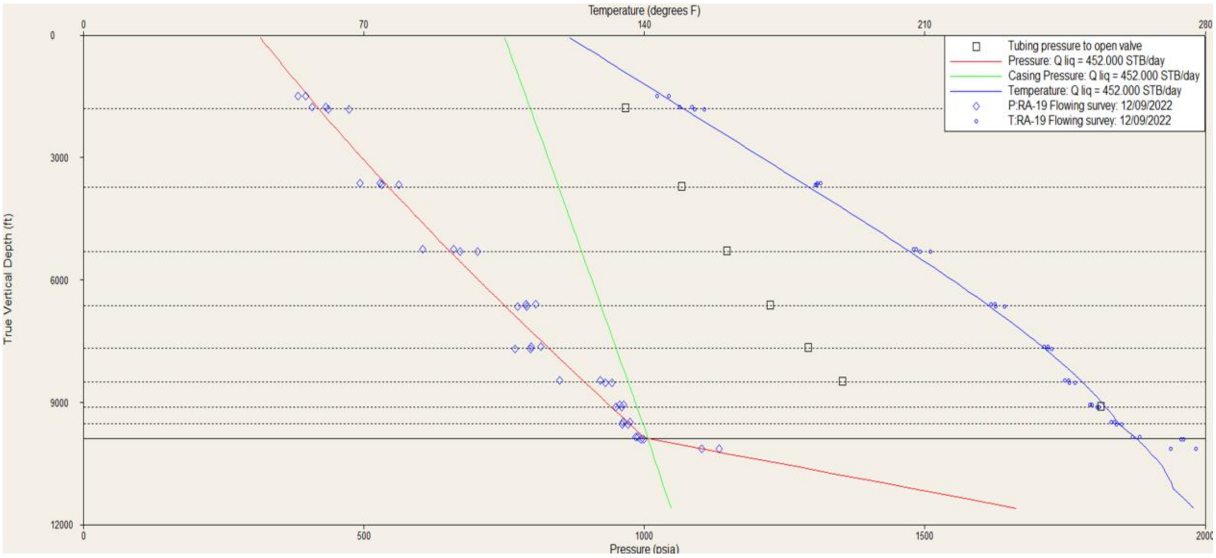


Figure 9. Flowing gradient survey – FGS

The survey can be executed in static or flowing well conditions. Changes in recorded pressure and temperature gradients further interpreted to representative offloading points or gas-liquid interface.

Static gradient survey (SGS) provides information regarding the static pressure and temperature which is typically used to evaluate inflow performance. Transient analysis of the pressure trend immediately after shut-in, provides information regarding the formation skin around the wellbore.

Flowing gradient survey (FGS) is used to determine the lifting depths. Survey points taken just under and over side pocket mandrels (SPMs) where the gaslift valves are installed, uncovering the valve status. Operating or leaking valves will be characterized with a temperature drop due to gaslift injection. By recording the temperature under and over valves depth, one can evaluate if a valve is passing or backchecked. Further, the change in pressure gradient will indicate the deepest offloading point, due to significant change in produced fluid density for the fluid mixed with gaslift and reservoir fluid.

The data provided by SGS and FGS is typically used to calibrate well models and uncover optimization opportunities by improving the inflow performance and vertical lift.

The data recorded by the calibrated memory gauge is highly accurate. Nevertheless, operational limitations apply on surveying live wells for gradients. A temporary shut-in is required during rig-up of the wireline equipment. This may result in changes of downhole condition. Pressure operated gaslift valves, such as PPO and IPO valves, may change status due to pressure changes resulted by temporary shut in. In addition, high flow rate wells may require choking of flow to be able to descend to the target depth. Choking of the well during flowing gradient survey may also result in change of downhole condition compared to higher flow and generate not representative surveillance data. Lastly, memory gauge requires stabilization time to record accurate reading. Gradient surveys are often deployed under time constraints. Stops to record the required data increase survey duration and time inside the well, which should be minimized. This limitation can result in logging data only across certain SPMs and do not provide information for the complete tubing profile. Tubing leaks between the SPMs are often undetected using this method. Minor leaks or valves passing restricted amount of gaslift, might also be undetected, due to minimal temperature drop resulted by restricted flow.

Flowing and static gradient surveys are frequently deployed on aging gas lifted fields with limited downhole instrumentation. This deployment requires increased resources and introduces additional operational risk due to the interventional nature of the service. Wireline and slickline crews are deployed for multiple purposes in well operations and may result in operational bottlenecks requiring attention to ensure operational efficiency.

3.4.3 Intervention-less methods for gaslift surveillance

For more than thirty years, the industry has discussed the use of tracers in gaslift surveillance activities. However, only in recent years has the technology advanced to support comprehensive diagnostics. The well intervention-less tracer surveillance system (WITSS) comprises of a compact multi-method approach that combines enhanced monitoring technologies such as acoustic surveys, tracer fingerprint analysis, compositional profiling coupled with independent temperature and gas rate measurements (Cornwall, Shkorin, Guzman, & El-Majzoub, 2021).

The method comprises injecting a Nitrogen tracer medium into the well's gaslift supply, while monitoring compositional variations of the injected and produced gas streams downstream of the injection point. The compositional data collected, together with surface pressures, temperatures, and acoustic response, is further processed in a proprietary software, tuning production parameters and identifying the gaslift injection rate and downhole gaslift distribution for each well.

Main deliverables of intervention-less surveillance methods are:

- Downhole gaslift distribution
- Gaslift injection rate
- Produced gas rate
- Compositional trend of lift and produced gasses
- Shut-in and flowing bottom hole pressures

3.4.3.1 Downhole gas-lift distribution

The distribution of gaslift downhole derived from tracer travel time, measured from the injection into the gaslift supply until its arrival to the detection point on the production tubing on the wellhead.

The model calculates the transport of a tracer gas in the annulus from the injection point to the gaslift valves (or potential leak points). The solution is found by dividing the annulus and tubing volume into a given number of grid boxes and solving the mass and momentum conservation equations iteratively for each box (Figure 10. Tracer propagational model).

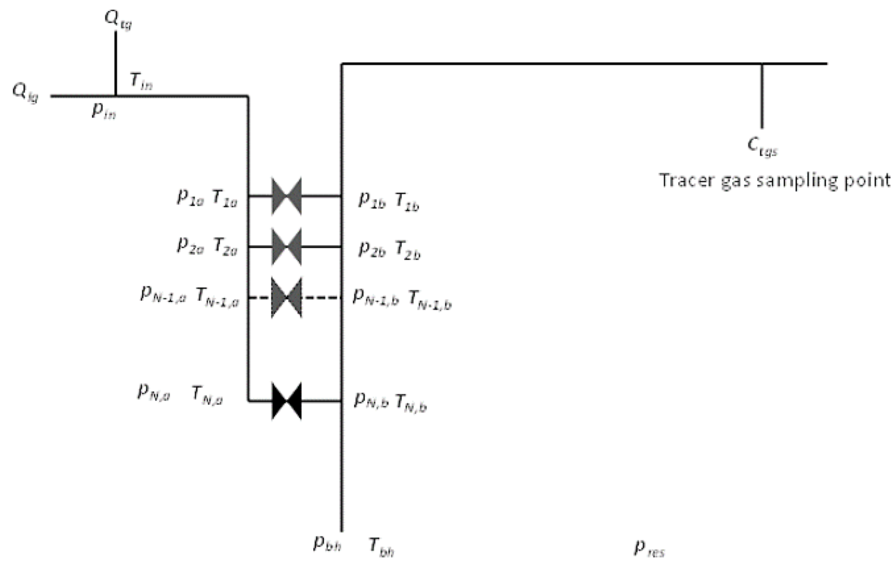


Figure 10. Tracer propagational model

The model calculates the transport of lift and tracer gases in an annulus from the injection point to the gaslift valves / leak points. Injection pressure and rate are known, so the transport of fluids during a given time step is first calculated for the uppermost box below the injection point. Then, the output of each box (pressure, velocity, and mass balance) is the input for solving the next box. When the gas mixture reaches the intermediate gaslift valves, a fraction of the gas mass is injected in the tubing, the remaining gas will be displaced further down the annulus. The calculation is repeated until the tracer gas reaches the lowermost gaslift valve or injection point.

The tubing model is a two-fluid model with distinct velocities for the liquid phase and the gas phase. The relationship between the liquid and gas velocities is given by a closure law (drift-flux model). The boundary condition is the well-head pressure. The reservoir production is assumed to be constant initially. The production index is calculated from the given produced oil rate, water cut, GOR, reservoir pressure, and initial downhole pressure. Mass and momentum equations are solved by numerical integration from bottom to top.

The tubing model is coupled with the annulus model and determines at each time step the mass of lift gas and/or tracer gas that is injected in the tubing through the gaslift valves or leak points. The downhole tubing pressure calculated at each time step is then used to calculate the produced rate in the next time step.

The lifting depth is determined based on the round-trip travel time of the tracer gas. The area underneath the return peak of the tracer is used to determine the amount of tracer returning from one or more lifting depths. Any loss of tracer is detected by calculating the mass balance of the system. A simulation of tracer travel time is compared to measured results, uncovering the lifting depth for each return. A mass balance analysis of return size correlates to the flow rate from each depth (Figure 11. Simulated and measured tracer travel time) (Cornwall, Shkorin, Guzman, & El-Majzoub, 2021, p. 6).

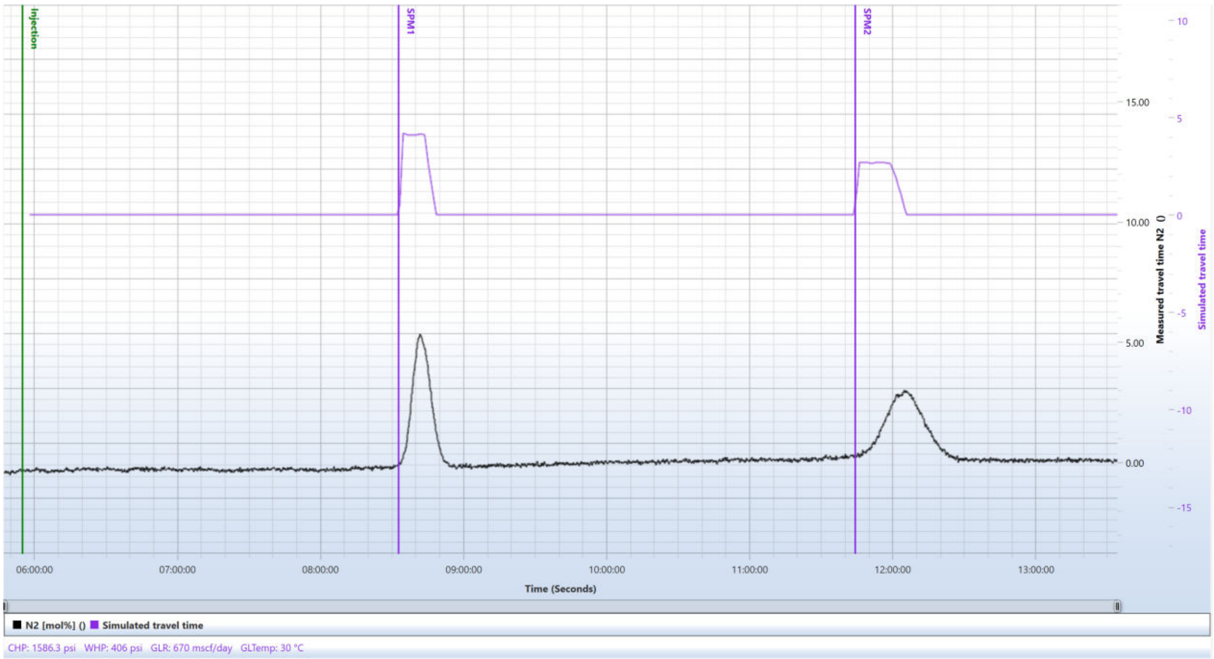


Figure 11. Simulated and measured tracer travel time

3.4.3.2 Gas lift injection rate

Gas lift injection rate (GLIR) can be measured using dilution principle. The tracer gas dilution method (TGDM) as outlined in ASTM Standard E 2029–99 (Standard Test Method for Volumetric and Mass Flow Rate Measurement in a Duct Using Tracer Gas Dilution, u.d.) uses constant injection technique. In this method, a known concentration of tracer gas is injected at a consistent rate into an upstream location of the flow stream. The tracer gas then becomes thoroughly mixed and diluted. Once steady-state conditions are achieved, the diluted volume fraction of the tracer gas is measured at a downstream location. Accurate implementation of the constant-injection technique requires accurate metering of the injected tracer gas, uniform mixing of the tracer gas into the transport stream, and accurate detection of the diluted tracer gas. When these requirements are met, the volume flow in the duct can be determined using the following equation: [5-7]:

$$M_{tr,i} = \int_{t_{d1}}^{t_{d2}} m_{tr}(t)dt = \int_{t_{d1}}^{t_{d2}} m_{g,d}(t)\left[c_{tr,d}(t) - c_{tr2,d}\right]dt$$

[5]

$$M_{tr,i} = \rho_{gs} \int_{t_{d1}}^{t_{d2}} Q_{gs,d}(t)\left[c_{tr,d}(t) - c_{tr2,d}\right]dt$$

[6]

$$Q_{gs,d} = Q_{gs} = \frac{M_{tr,i}}{\rho_{gs} \int_{t_{d1}}^{t_{d2}} \left[c_{tr,d}(t) - c_{tr2,d}\right]dt}$$

[7]

Where:

$M_{tr,i}$ – mass of injected tracer

m_{tr} – mass rate of injected tracer

$c_{tr,d}$ – tracer component concentration at the detection location

$c_{tr2,d}$ – tracer component concentration prior the injection (base line)

ρ_{gs} – standard density of flow stream (lift gas)

$m_{g,d}$ – mass flow rate at the detection location (lift gas mass rate)

$Q_{gs,d}$ – volumetric flow rate at the detection location (lift gas vol. flow)

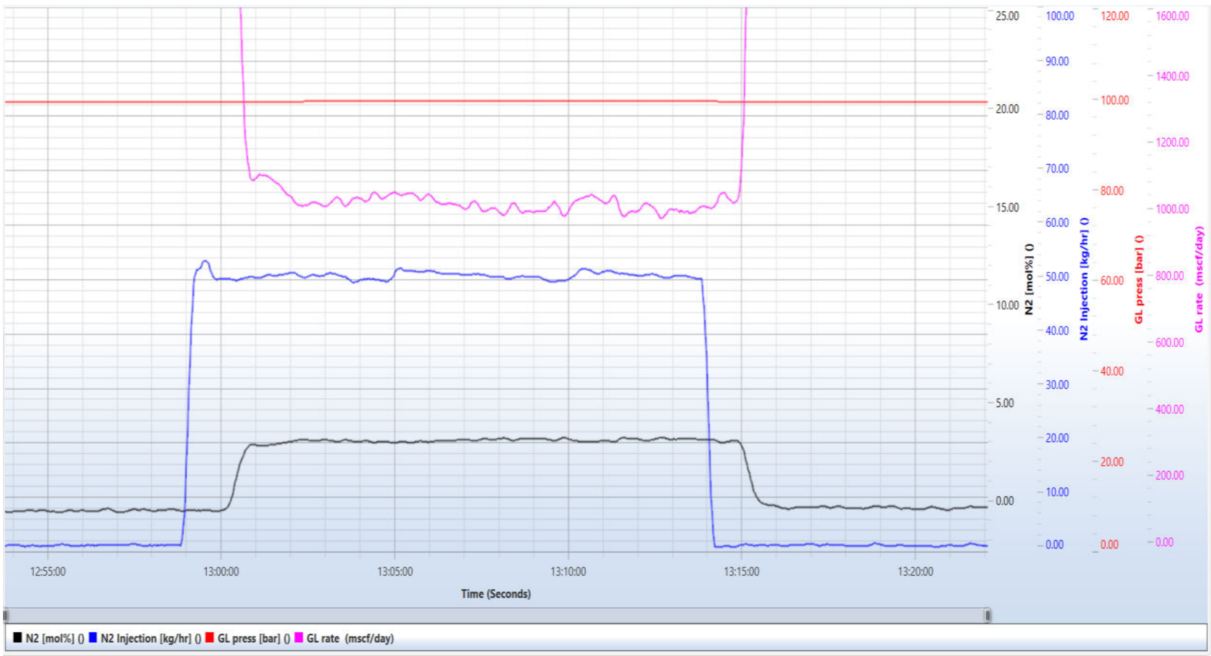


Figure 12. Gas lift dilution measurement

Gaslift dilution measurement provides information regarding the gaslift rate during the measurement itself. The measurement is restricted in time, due to the operational limitation for continuous dilutant injection upstream. In order to evaluate the trend of injected gaslift throughout the survey, ultrasonic flowmeter is used to log the gaslift velocity of the well. Gaslift velocity obtained by the ultra-sonic measurement is further converted to representative volumetric rate. This method requires a measurement of the cross-sectional area which can be a significant source of error if the shape and dimensions of the sampling section cannot be determined with sufficient accuracy. By using the rate derived from dilution measurement, rate reported from the ultra-sonic meter is calibrated, providing reliable data for gaslift injection trend throughout the survey (Figure 13. Ultra-sonic gas lift rate) (Cornwall, Shkorin, Guzman, & El-Majzoub, 2021, p. 11).

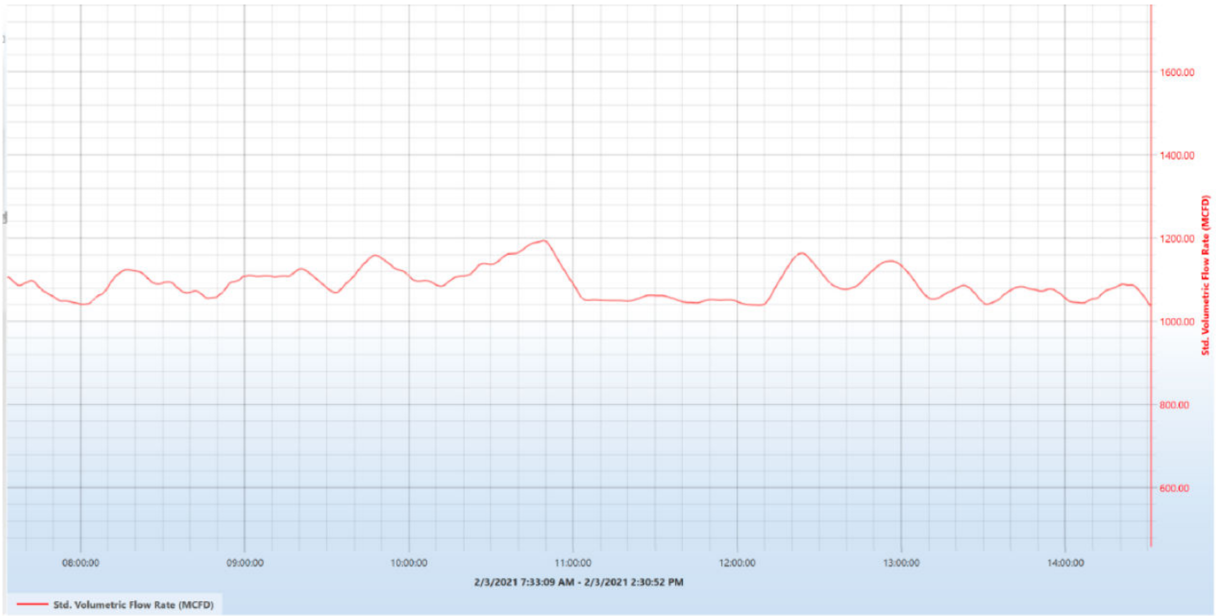


Figure 13. Ultra-sonic gas lift rate

Dilution techniques for measuring flow have been used in different industries for some time. The gaslift application is relatively new and has limited published information so far. This makes it challenging to estimate the accuracy of this measurement applied directly on gaslift. Rodney A. Bryant performed a study of uncertainty estimates of tracer gas dilution flow measurements in largescale exhaust ducts (Bryant, Volume 61, June 2018). The constant-injection technique of the tracer gas dilution method was applied in the duct of a large-scale flue gas exhaust system. An estimate of the measurement uncertainty for this application of the method was computed, evaluating the degree of tracer mixing, and measuring the repeatability of the test method. The results showed the relative expanded uncertainty of the volume flow measurement using the tracer gas dilution method was on average ± 0.028 and typically less than ± 0.035. Measurement uncertainty for the diluted volume fraction of tracer had the greatest contribution to the combined uncertainty, followed by the measurement repeatability, and the degree of mixing.

3.4.3.3 Produced gas rate

The produced gas rate is derived from analyzing the area generated under the concentration trend due to the tracer return (Figure 14. Produced gas). Considering that all the injected tracer is detected when produced, the sum of the area under each return is proportional to volumetric rate of total gas produced during the detected return [8].

$$\frac{M_{tr,i}}{M_{prod.g}} = \frac{\sum A_{tracer}}{\sum A_{total}}$$

[8]

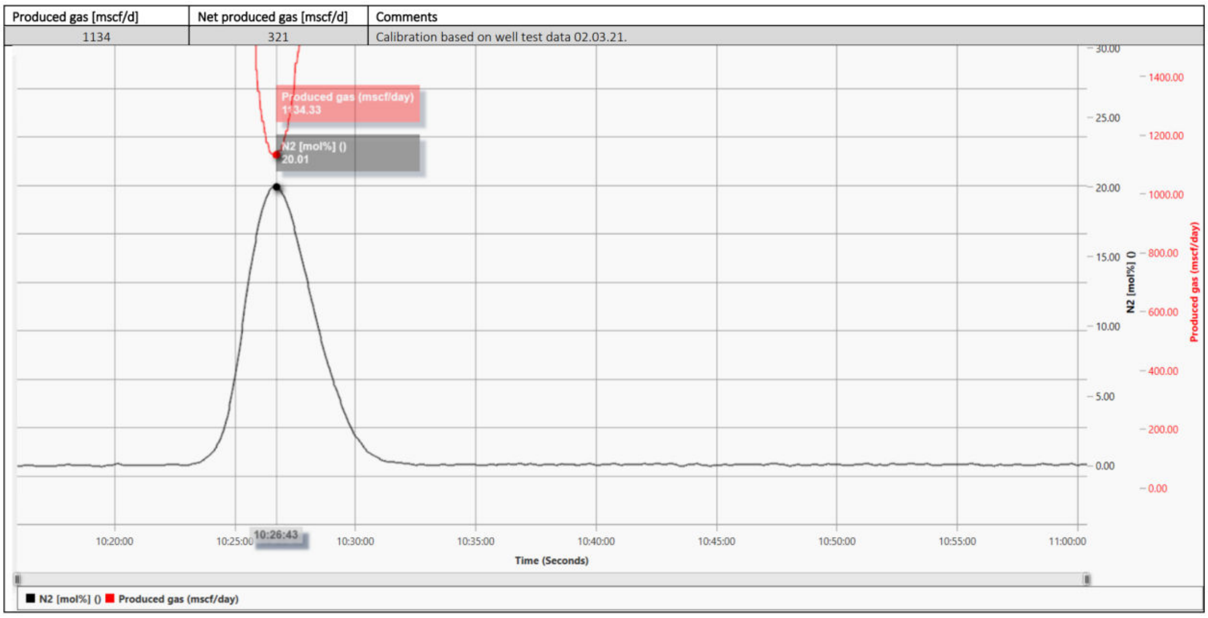


Figure 14. Produced gas

3.4.3.4 Shut-in bottom hole pressures

Intervention-less techniques for determination of static bottom-hole pressure are based on acoustic measurement of gas-liquid interface downhole (Figure 15. Acoustic measurement), and calculation of hydrostatic column based on gas and liquid gradients.

Acoustic methods are commonly used to determine the liquid level in a well. A manifold with pressurized gas is used to generate a pressure pulse at the surface. Alternatively, a blank cartridge can be used for the same purpose. The pulse is then reflected and recorded as echoes from collars, obstructions, and the gas-liquid interface.

For wells with pressures below 100 psi, the gas gun volume chamber is pressurized to about 100 psi above the well pressure, and then the gas is rapidly released into the well to create the pressure pulse. On the other hand, for wells with pressures exceeding 100 psi, the volume chamber in the gas gun is bled to a pressure lower than the well pressure. Then, a valve is quickly opened to allow wellhead pressure to expand into the volume chamber, creating a rarefaction pressure wave.

A microphone is used to convert the pressure pulses reflected by collars, liquid, and other obstructions (or changes in cross-sectional area) into electrical signals. These signals are then amplified, filtered, and recorded on a strip chart for analysis (Figure 15. Acoustic measurement). The depth of the liquid level can be determined by recording the time to the liquid-level reflection, and calculating representative acoustic velocity derived from equation of state (McCoy, Podio, & Huddleston).

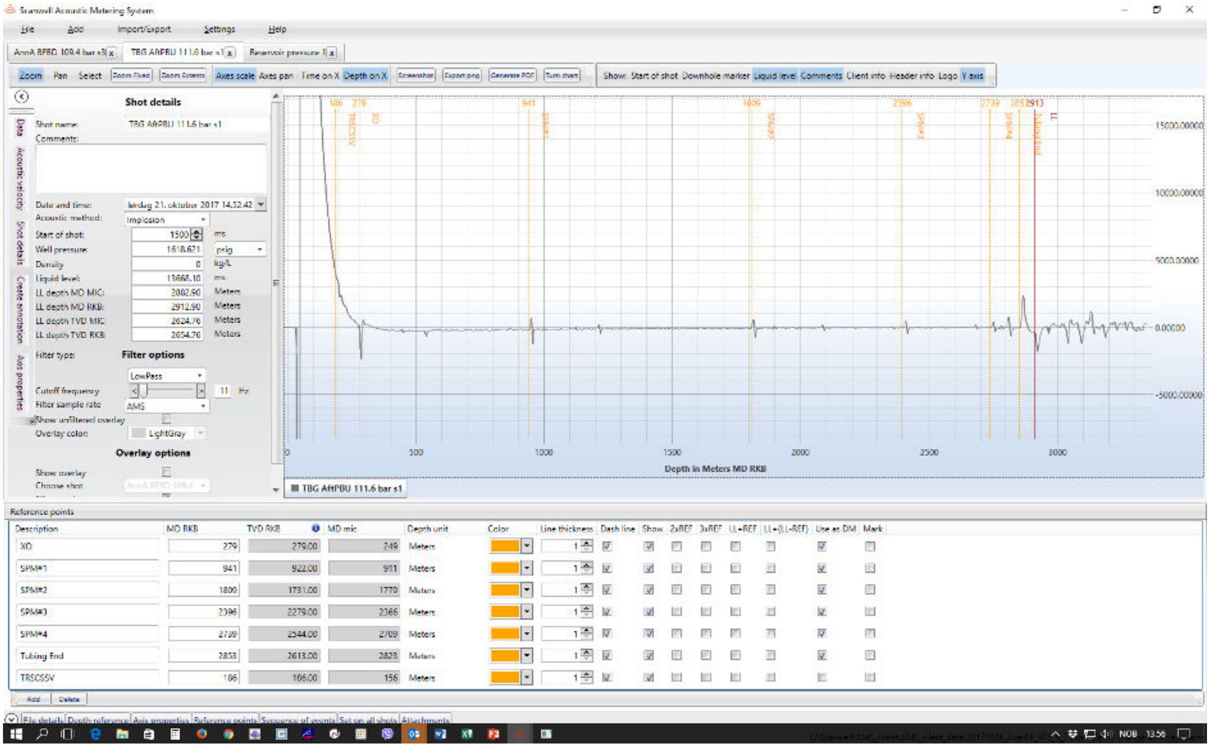


Figure 15. Acoustic measurement

Gas gradient is typically calculated using equation of state (EoS). Average values for pressure, temperature and gas composition shall represent the average gradient/density of the column. Pressure at gas-liquid interface/liquid level is than determined by equation [9].

$$P_{liquid\ level} = P_{wh} + \rho_{avg} g h_{gas}$$

[9]

Nasser M. Al-Hajri; Sidqi A. Abu-Khamsin; Mohammed D. Al-Ajmi in their work suggested that using average values for pressure, temperature and compressibility factor are not suitable for wet gas wells due to the variation in gas composition and gravity with changes in the wellbore pressure and temperature if the dew point line is crossed. Variation of gas gravity affects the accuracy of pseudocritical, and thus pseudo-reduced, pressure and temperature values. Consequently, the gas z-factor value will be affected as well (Al-Hajri, Abu-Khamsin, & Al-Ajmi, (2019)). They proposed a method with the use of apparent molecular weight profiling, which captures changes in gas gravity within the wellbore. Hence, the pressure calculations are performed based on true values of pseudocritical and pseudo-reduced pressures and temperatures. This enables proper simulation of z-factor changes inside the wet gas column.

Data from 75 gas wells was collected. These wells produced from five reservoirs distributed over five fields with varying properties. For each well test, the data includes field pressure and temperature measurements across multiple depths within the wellbore. The data set was quality controlled to exclude wells inapplicable to the top node SBHP calculation method. The results of the method showed relatively small error compared to the actual field measurements. These average values (Figure 16. Calculating BHP by apparent MW profiling), produced by the Brill and Beggs-Standing combi nation of correlations, was found to be the lowest among six other tested combinations (Al-Hajri, Abu-Khamsin, & Al-Ajmi, (2019)).

	Absolute pressure difference (psia)	Absolute relative error (%)
Average	78.78	1.71
Minimum	0.20	0.00
Maximum	217.78	5.68

Figure 16. Calculating BHP by apparent MW profiling

The liquid gradient can be calculated from wells production and PVT data or measured directly onsite. The onsite measurement can be performed by increasing the tubing head pressure (THP) with either gaslift or other pressurized gas, while monitoring the liquid level movement with use of acoustic measurements. Further, the liquid gradient is calculated from following equation [10].

$$Liquid\ gradient\ = P_{WH2} - P_{WH1} \,/\, LL2 - LL1$$

[10]

Where:

$P_{WH2} - P_{WH1}$ change in tubing head pressure

$LL2 - LL1$ change in liquid level depth

The results from the acoustic measurements can be aligned in a commercial software, visualizing the results (Figure 17. Static bottom-hole pressure).

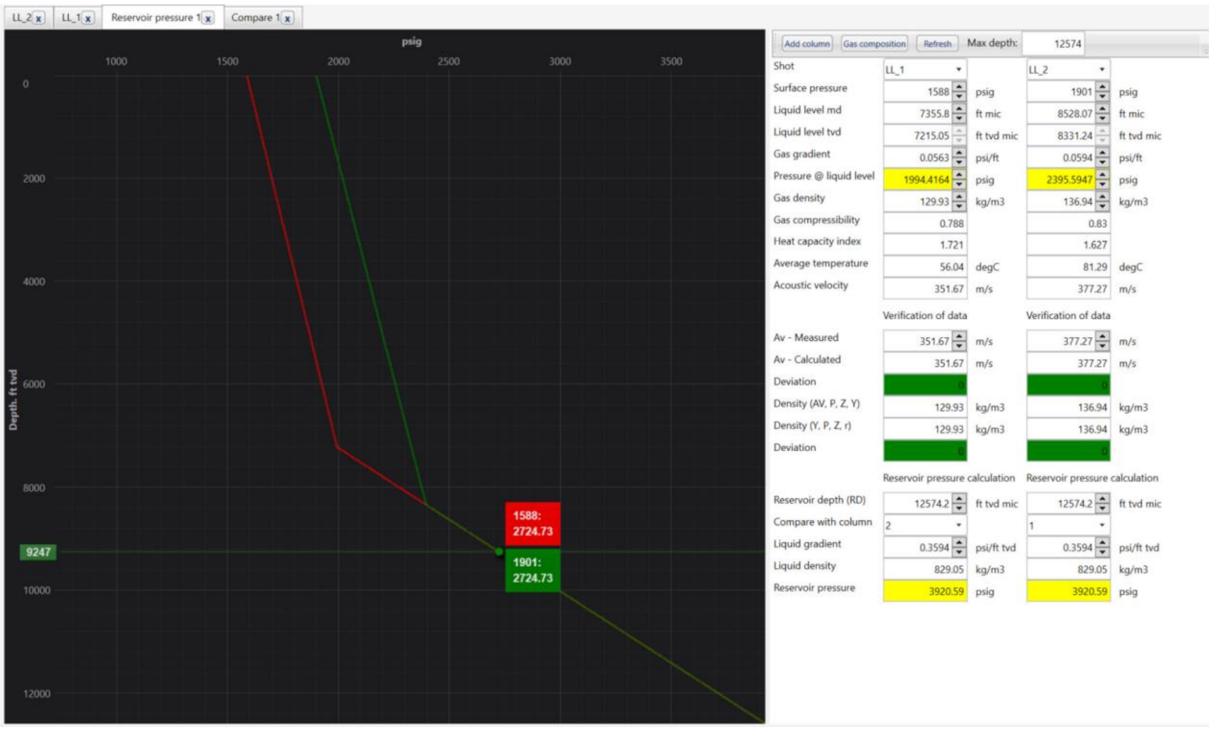


Figure 17. Static bottom-hole pressure

The static bottomhole pressure is the sum of surface pressure, gas column pressure, and liquid column pressure. The accuracy of each of these pressures determines the accuracy of the static bottomhole pressure. (McCoy, Podio, & Huddleston).

McCoy, Podio and Huddleston further compared the acoustic method suggested in their paper to reference data measured with downhole gauge concluding high accuracy of the proposed method (Figure 18. Acoustic BHP).

TABLE 2

ACOUSTIC AND MEASURED (BOMB) PRESSURE DATA

DEPTH, FEET	SURFACE PRESSURE, PSIG	ACOUSTIC BOTTOM-HOLE PRESSURE, PSIG	BOTTOM-HOLE PRESSURE, BOMB NO. 1 PSIG	BOTTOM-HOLE PRESSURE, BOMB NO. 2 PSIG
10,600	5,610	7,585	7,583	—
10,600	6,065	7,864	7,874	—
9,736	5,012	6,005	5,954	—
13,792	8,485	10,294	10,347	10,425
9,359	1,193	1,467	1,459 (QUARTZ)	—
8,956	1,440	1,760	1,751 (QUARTZ)	—

Figure 18. Acoustic BHP

3.4.3.5 Flowing bottom-hole pressure

Flowing bottom-hole pressure is determined using either empirical or mechanistical correlation. Flow up the tubing is multiphase. Gas and liquid tend to separate and will normally not travel with the same velocities, hence slip relations are often considered for better accuracy. Both temperature and pressure conditions will change in upwards multiphase flow. Accurate prediction of pressure drop in oil and gas wells is needed to forecast well deliverability. Many multiphase flow correlations are available for commercial use. Still, not many of them are proven to give good results for all conditions that may occur when producing hydrocarbons. Comparing available correlations to reference data is often the best way to determine which one to use. Most of the correlations available are to some degree empirical and will thereby be limited to conditions of which the correlations are based on (Fossmark, 2011, p. 1).

Fossmark further showed in her study, the average percentage error for 17 correlations using 203 tests. It shows that HB, FB, PE, PE2 and PE3 give the lowest percentage error (Figure 19. Total average error in predicted pressure drops). The standard deviation is also smallest for these correlations, meaning they are consistent. They all lie within 10 % error, which is regarded as acceptable. BB and MB give the highest percentage error. (Fossmark, 2011, p. 59).

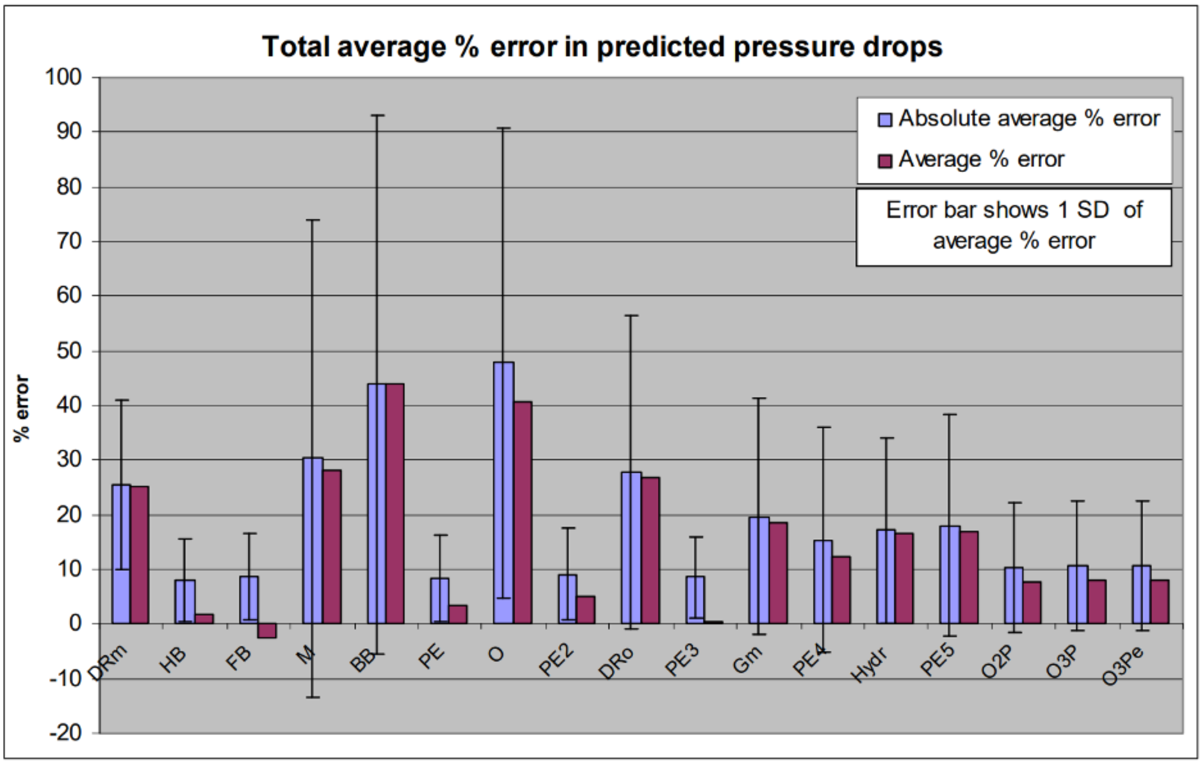


Figure 19. Total average error in predicted pressure drops

Lower pressure drops are predicted for gas lifted wells, due to lighter hydrostatic column. When there is high uncertainty in gaslift rate, the correlations seem to give a relative shift in pressure. Close to perfect match may be the result of cancelling errors. This was observed especially for Gray Modified (Gm), PE5 and the OLGAS correlations, for tests including gaslift. Both too high and too low pressures were predicted, giving a close to zero percentage error (Fossmark, 2011, p. 61).

Additional work comparing calculated and measured BHFP was presented by Cornwall (Cornwall, Shkorin, Guzman, & El-Majzoub, 2021, p. 23) comparing accuracy of mechanistic Hassan Kabir calculation (Hasan & Kabir, 1999), tuned with accurate GLIR and downhole gaslift distribution, showed similar accuracy within 10% for tested wells (Figure 20. Measured vs calculated BHFP).

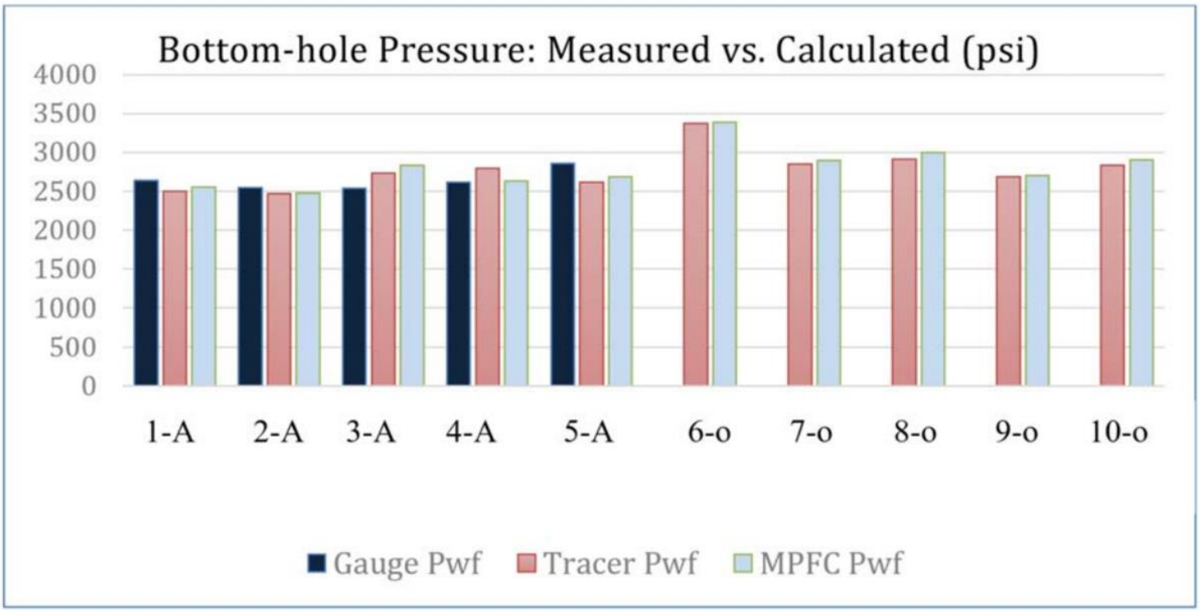


Figure 20. Measured vs calculated BHFP

Tuning and further development of empirical and mechanistic flow models allow to reduce the uncertainties to 5% range. Work presented in Unified Mechanistic Model for Steady-State Two-Phase Flow showed results with a −1.3% average error, a 5.5% absolute average error and 6.2 standard deviation. (Gomez, Shoham, Schmidt, Chokshi, & Northug, 2000).

4. Constructing the decision model

4.1Background

The decision model presented in this work, based on the results from a field trial in which intervention-based service was directly compared to intervention-less service by applying the method on same wells and comparing the results. The results from the field trial were further published in SPE-208003-MS "Unlocking Opportunities for Gas Lift Well Surveillance - Building the Framework for Consolidated Data Capture and Processing" (Cornwall, Shkorin, Guzman, & El-Majzoub, 2021). The decision model constructed in this thesis, considering the published results but did not have direct input from the decision-maker except the mentioned publication. The value functions and the objective hierarchy developed in the decision model are based on the decision analysis theory and not necessarily the exact presentation of the decision process related to the same field trial.

4.2 Decision context

Gaslift operations are highly dependent on data quality and team competence to operate the asset efficiently. As a field matures, the greater demand for lift gas in conjunction with limitations imposed by existing facilities and prevailing operating conditions (compression capacity, lift gas availability, well shut-in for workover, etc.) can prevent optimal production from being achieved. Lack of reliable surveillance data or capacity limitations of utilized field resources for surveillance activities contribute further to undetected optimization opportunities.

The first step should be mapping the bottlenecks for optimum production. Choices such as upgrading compression or production facilities, installing instrumentation and infrastructure for high-frequency reliable surveillance data, or increasing ad-hoc surveillance activities on producing wells, can all contribute to improving the production from the asset.

Financial strategies for allocating capital and operational expenditures are often related to the risk associated with financing one or the other. Capital expenditures (CAPEX) to upgrade facilities and infrastructure, often require significant investments, and carry inherent uncertainty in calculation of net present value (NPV). The cost of financing large capital expenditures is often uncertain as well as return on the investment period.

Operational expenditure (OPEX), on the other hand, is characterized by reduced financial risk and does not require initial investments. Risk averse attitude for allocating capital will often prioritize optimizing operational expenditure even though the calculated NPV from CAPEX investments can result in a higher value.

The decision model presented in this thesis does not consider alternatives related to capital expenditures for upgrading the compression and production facilities, installing new infrastructure across the field, work over activities or drilling new wells. The context of the decision process drafted in this work is related to surveillance activities on producing wells and the challenge of comparing and choosing between intervention-based and intervention-less approach for that activity.

Two main technical challenges arise addressing gaslift optimization of the producing wells. First, is the allocation of available gaslift between the producers. Each well has its optimum and desirable gaslift injection rate. However, when the entire gathering network is considered, the optimal gaslift injection rate differs from that which maximizes individual well production. This due to the back pressure effects (the pressure drop observed across flow lines) imposed by common tie-backs further downstream. Effective lift gas allocation is a continuous process, considering constantly changing operational realities. High frequency surveillance data allows for planning and effective utilization of changing demand in gaslift supply caused by continuous well operations.

Second, stems from gaslift design and the actual distribution of injected lift gas downhole. Redesigning well configuration, changing faulty gaslift valves, and addressing downhole integrity issues, allows additional production gain and reduced down-time.

4.3 Objectives and goals

Structuring objectives and goals is a step that helps the decision-maker to understand and to further communicate within the organization why we care and should spend resources on that particular decision. The structuring process by Brownly (Brownly, 2013, p. 26) is a three-step process:

1. Separate fundamentals from mean objectives
2. Arrange the hierarchy of the objectives
3. Decide when to stop the structuring process

The fundamental goals as the main objectives or purpose that guides operations and decision-making. The are many aspects of oil and gas operation that can be argued as fundamental values and objectives. Values such as energy security and national interests, safety standards for its workforce and communities, long term environmental goals, sustainability, and contribution to local economic development - can all be arguably placed on top of objective hierarchy. In this thesis the assumed fundamental goal of the presented decision is to maximize shareholder value.

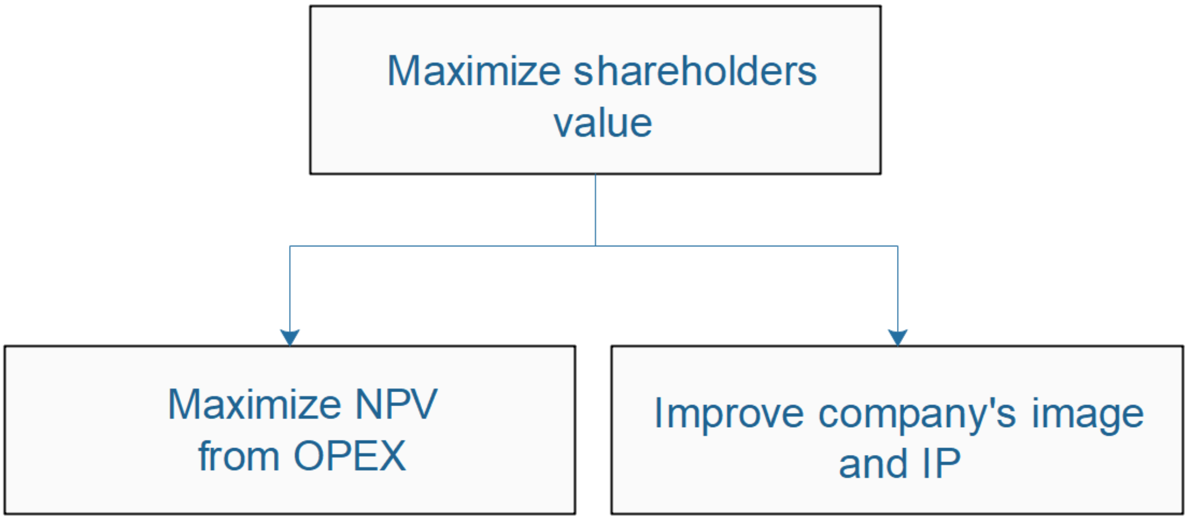


Figure 21. Fundamental goals

The hierarchy structure of fundamental goals (Figure 21. Fundamental goals), assumes two paths to maximize shareholder value – maximizing value from operational expenditures (OPEX) and improving company's image and intellectual property (IP). The objectives related to OPEX will be further addressed as 'Direct Value Objectives' and the objectives related to company's image and IP will be addressed as 'Indirect Value Objectives'.

Moving down the hierarchy, the low-level objectives describe and clarify the fundamental top-level objective.

The 'Direct value objectives' related to maximizing value from operational expenditures (OPEX) presented in Figure 22. Hierarchical structure OPEX.

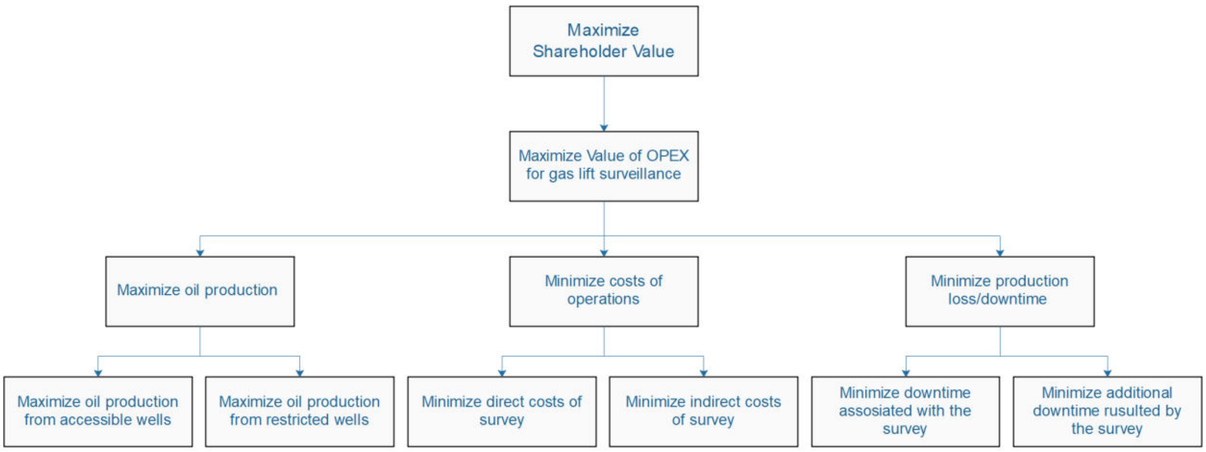


Figure 22. Hierarchical structure OPEX

Considering the context of the decision drafted in previous section. The lower-level objectives for maximizing value from operational expenditures (OPEX) are to optimize production, minimize downtime and the cost of the operations (Figure 22. Hierarchical structure). One should further divide each of those objectives into a lower-level category if the nature of the alternatives or the evaluation measures suit a more detailed categorization of the objectives.

Assuming the preferences of the decision maker and the context of the decision, the objective for maximizing production is further divided into maximizing production from accessible and restricted wells.

With respect to minimizing operational costs, the lower-level objectives are minimizing the direct and indirect cost of the survey. Direct cost related to the cost associated with the survey itself, while indirect cost associated with additional costs that can arise from the survey. For example, if the survey result in damage to the well and additional costs required to put the well back in production, or on a country, additional data gathered during the survey can result in savings if this data is usually associated with independent operational cost.

To better understand downtime objective, the category divided into downtime associated with the execution of the survey, such as required shut-in for rig-up or rig-down purposes, in addition to degree of chocking the well to be able to execute the survey. And possible downtime resulted due to an undesired event associated with the operation. For instance, if the well is damaged and cannot be produced after the execution of the survey.

Although the MODA framework defined by brownly (Figure 2. Decision-making process (Brownly)) suggests identifying objectives prior identifying alternatives, the work of building the hierarchical structure of the objectives (Figure 22. Hierarchical structure OPEX) is directly related to those. The alternatives in this case are known in advance, and characterized by different technical features, therefore the lower-level objectives are constructed in a way that allows to compare the alternatives on a common scale. The structuring process of the objective should continue until the lower-level objectives can be specified by a set of evaluation measures.

The 'Indirect value objectives' related to improving company's image and intellectual property (IP) presented in Figure 23. Hierarchical structure - CI.

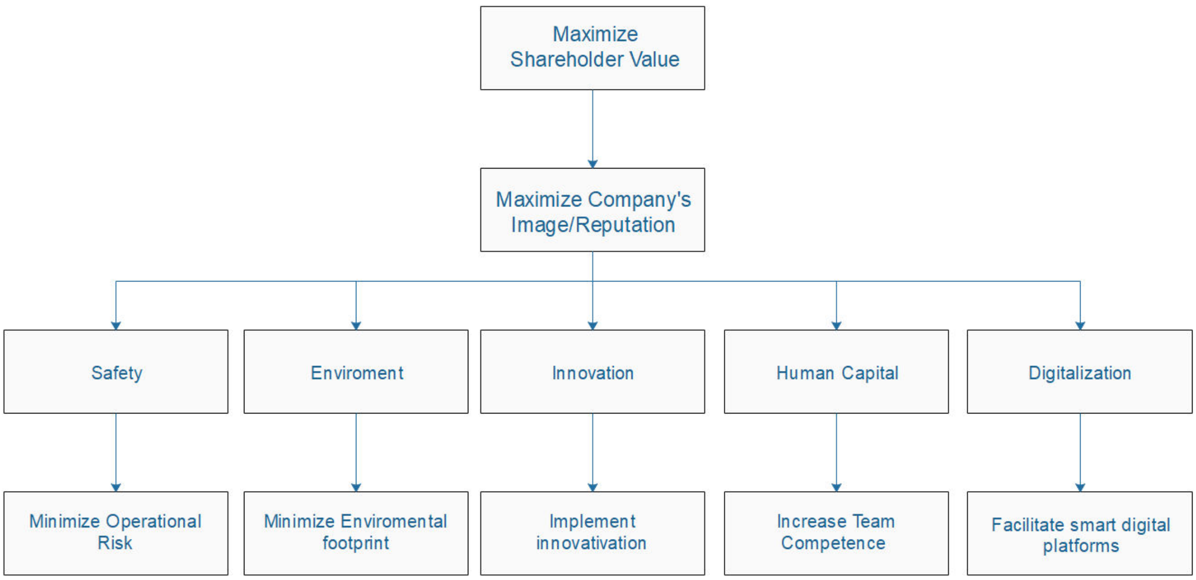


Figure 23. Hierarchical structure - CI

To maximize the company image and intellectual property, the lower-level objectives would be typically related to the company's vision and goals. The decision model presented in this thesis considers objectives such as safety, environment, innovation, human capital, and digitalization as metrics for image and intellectual property.

As a result of structuring the objectives, the decision maker identifies measurable paths to the fundamental goal associated with the decision. The next step is to identify and construct desired evaluation measures for the identified objectives.

4.4 Preferences over evaluation measures

Evaluation measures help the decision maker to quantify the extent to which the objectives are achieved. The functions of the evaluation measures must suit the scale on which each objective is evaluated. For continuous scales, such as profit, costs, production gain or loss – either linear or exponential functions can be used. For scales representing a few discrete levels, such as level client satisfaction, level of operational risk etc. – piecewise linear functions are applicable.

In the context of maximizing the 'direct value objectives', such as maximizing production and minimizing costs. Those can be measured by natural evaluation measures with the help of continuous exponential or linear value functions. The outcomes can be easily measured directly by comparing production gain and loss in terms of barrels per day, or service cost in USD (Figure 22. Hierarchical structure OPEX).

A continuous exponential value function is based on equation depending on the range of the evaluation measure and exponential constant ρ (rho). This constant determines the shape of the exponential function. Large values of ρ force the function toward a line, small value of ρ makes the function extremely curved. Positive ρ represent concave functions for decreasing return-to-scale, negative ρ will result in convex function for increasing return-to-scale. The decision-maker can specify either increasing preference for value when objectives describe profits or production gain, or decreasing preference values for objectives such as costs and production loss. To adjust the exponential constant ρ, the decision-maker shall specify the mid-value of evaluation range, which is the point at which the increase in value from the minimum to mid-value is equal to increase from mid-value to maximum score (Brownly, 2013, p. 57).

A continuous linear value function is based on a linear equation. The slope represents constant change in value over the specified range.

The 'indirect values objectives' identified in objectives hierarchy (Figure 23. Hierarchical structure - CI), contributing to company's image and IP, are not measurable by natural evaluation measures such as barrels per day or USD. Those to be measured by constructed evaluation measures with help of piecewise linear functions. The constructed measures for indirect values will be in form of levels, where the lowest level will represent the strongest negative impact on the value function and in a country the highest level will represent the highest positive impact.

Piecewise linear functions consist of line segments between each of the evaluation measure levels. To develop the function, the decision-maker specifies the relative change in value from one level to another (Brownly, 2013, p. 53).

4.4.1 Continuous functions

Continuous functions are chosen in this model to describe the value obtained from objectives related to production gain and service cost. The decision-maker would typically have an idea about the high and the low ranges for each objective and work towards a specified KPI which can be related to the curvature of the function. The range is continuous, and all the values within the range are possible. The functions are either increasing or decreasing (concave or convex) allowing to simulate correct value distribution from possible outcomes for the decision-maker. The input used in the presented decision model for continuous exponential value functions presented in Table 1. Direct value functions variables.

Continuous Value Functions				
	Production Gain	**Direct cost per Well**	**Indirect cost per well**	**Production Loss/Downtime**
High	150	$ 15,000.00	$ 15,000.00	1
Low	0	$ 5,000.00	$ - 100,000.00	0
Pref.	Increasing	Decreasing	Decreasing	Decreasing
rho	40	-3000	Linear	-0.07
Weight	50%	20%	10%	20%

Table 1. Direct value functions variables

The production gain function is an increasing concave function with a range from 0 to 150 barrels per day. The range is a function of the decision-maker assessment of the production gain possible to achieve from optimization survey. The function is increasing to describe increasing value from each additional barrel of oil gained. The degree of concavity is related to KPI targets for production gain, the value from the first barrels gained is larger than the last barrels within the range. The value function for production gain is calculated using the following equation [11].

$$V_{prod\_gain} = (1 - \exp\left[-\frac{prod.gain - Low}{\rho}\right])/(1 - \exp\left[-\frac{High - Low}{\rho}\right]) \qquad [\,11\,]$$

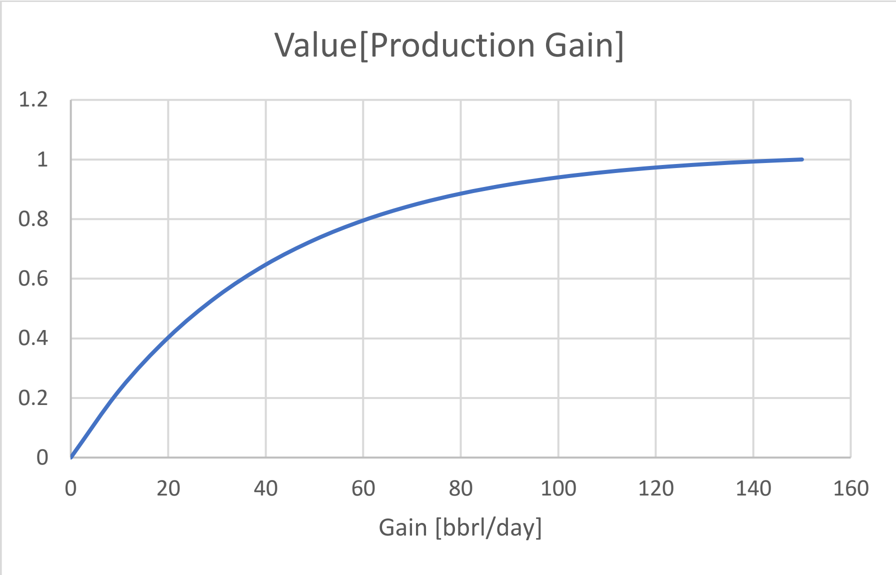


Figure 24. Production gain value function

The production loss value function is a decreasing exponential convex curve with a range from 0 to 1. The range represents fraction of production loss or downtime, resulted or associated with the survey. The function is very curved, which will represent decision-maker strong preference to avoid initial downtime (Figure 25. Production loss value function).

The function is calculated using the following formula [12]:

$$V_{prod\_loss} = (1 - \exp\left[-\frac{High - prod.loss}{\rho}\right])/(1 - \exp\left[-\frac{High - Low}{\rho}\right])$$

[12]

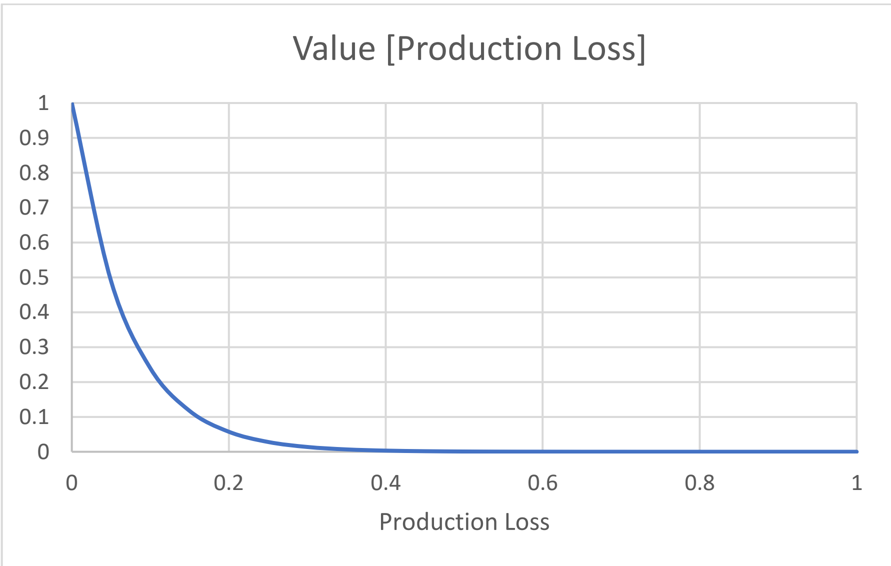


Figure 25. Production loss value function

Value function for direct service cost is a decreasing convex function with a range from 5-15 thousand USD, which is the estimated range for cost of gaslift surveillance survey. The value decreases with increased cost. I this case the target for the cost per well is 7000 usd (Figure 26. Service cost value function).

The function can be further calculated using the following formula [13]:

$$V_{service\_cost} = (1 - \exp\left[-\frac{High - ser.cost}{\rho}\right])/(1 - \exp\left[-\frac{High - Low}{\rho}\right])$$

[13]

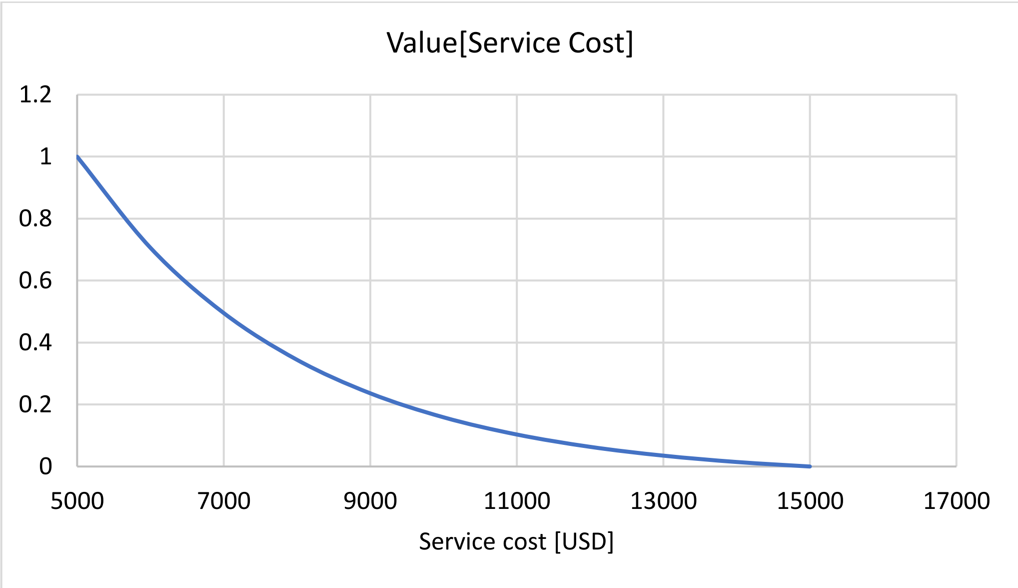


Figure 26. Service cost value function

Value function for indirect service cost is a decreasing is a decreasing linear function with range from -100000 to 15000. The range chosen covers an estimate for indirect cost associated with the survey. The function is linear, which represents constant increment in value over the range (Figure 27. Indirect service cost value function).

The function can be further calculated using the following formula [14]:

$$Value_{indirect} = -\frac{1}{High - Low}(indirect_{cost} - Low) + 1$$

[14]

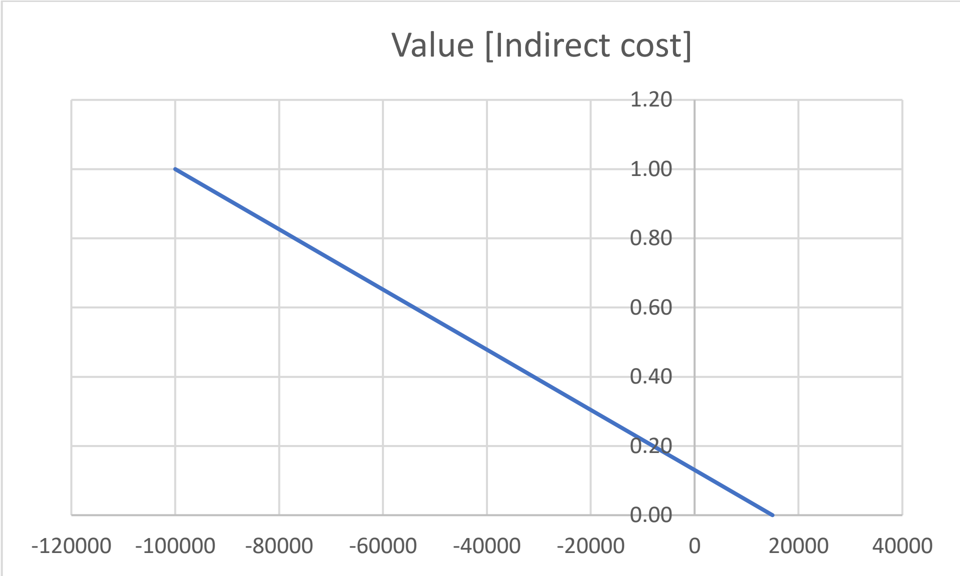


Figure 27. Indirect service cost value function

4.4.2 Piecewise linear functions

The indirect values identified in Figure 23. Hierarchical structure - CI, evaluated by piecewise linear functions. The score system proposed to evaluate indirect values, consists of discrete levels (0-4), the value from the representative score can be represented by either linear or piecewise linear functions. Linear functions would represent an evaluation level with constant return-to-scale, while piecewise linear functions are flexible enough to represent different return-to-scale over the evaluation levels.

In the piecewise function chosen for the decision model, the value obtained from the first level increase (0-1) is larger than the additional value obtained in the next two steps (1-3), but equal to the additional value of the last increase (3-4). The proposed value function describes a perspective of the decision-maker that evaluates indirect contribution of choosing gas-lift surveillance technique by discrete preference levels 0-4 (Figure 28. Piecewise linear value function). Each piece in this piecewise linear function $y = mx + b$ constructed by determining the slope (m) which represent the incremental value increase for each increase in level, and corresponding y-intercept (b).

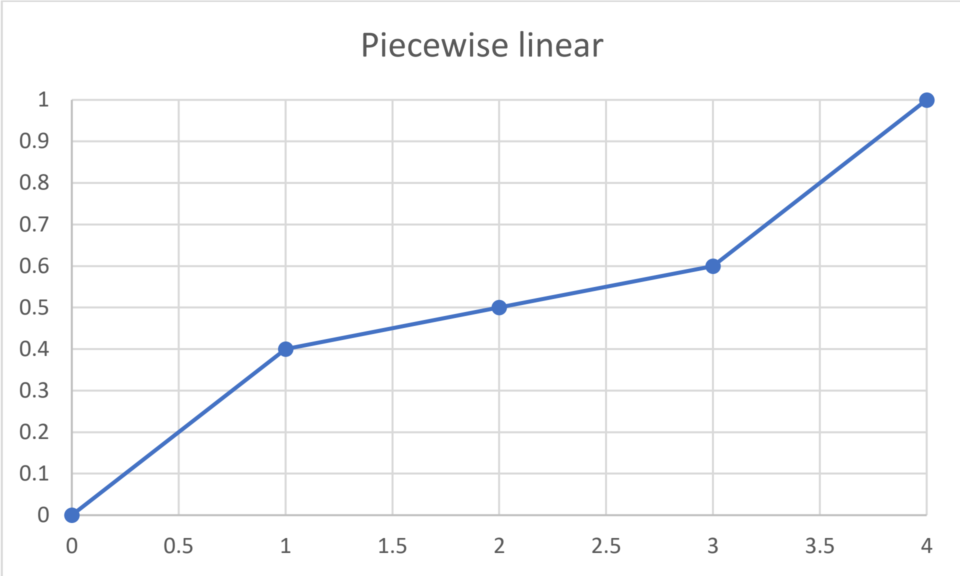


Figure 28. Piecewise linear value function

4.4.3 Weighing objectives

Preference weights are weighing factors that are applied on each of the objectives and they address the different degree of importance of the objectives for the decision-maker. The weights must sum to 1(100%) allowing the model to function.

The two paths for maximizing shareholder value presented in Figure 21. Fundamental goals) are weighted first. The decision-maker should carefully evaluate the importance of each fundamental objective based on own or organizational preferences. Organizations have different strategies that lead to maximizing shareholder value or any other fundamental objective.

Next step is to weigh the lower-level objectives in each of the paths. The sum of the weights must be again equal to 1 (100%).

Consider the direct value objectives from Figure 22. Hierarchical structure, related to production gain, loss, and service cost. The decision-maker must evaluate the importance of each objective. Production gain is the desired outcome of gaslift optimization activity, on the other hand – production loss associated with the survey has the opposite effect.

The cost of the survey is negligible considering the profit one can achieve from successful production optimization activity. But the production gain is uncertain, while the cost of survey is fixed. The weight allocated to survey cost should be evaluated against the risk of not gaining any production and generating possible production loss associated with the survey. Another point to consider is budgets that need to be requested and approved to implement surveillance strategies. The budgets need to align with the company's financial strategy and may be a significant factor when considering the relative weight of the survey cost.

The indirect value objectives from Figure 23. Hierarchical structure - CI, cannot be directly quantified in the same scale as production or cost. Those values have constructed evaluation measures in the form of levels, but the decision maker must decide on the importance of each objective relative to the others.

Indirect values are typically valued based on operational priorities and company strategies. Some organizations will prioritize reduction in operational risk higher than reduction in environmental footprint associated with the survey, and visa versa. Operational risk and environmental footprint can also carry direct costs associated with flaring, pollution and HSE related aspects and should be considered. Increasing team competence can have a direct impact on shareholders' value by increasing the organizational capacity to make good decisions. Innovation often is a desired property, but on the other hand results in limited competition and contractual challenges. Conventional services are characterized by better competition and availability but can limit the attempts to transit to new digital big data platforms.

4.5 Identifying alternatives

Operational budgets on aging brownfields are typically allocated to service companies providing troubleshooting and maintenance activities on the wells. Services such as wellhead maintenance, well intervention operations, integrity testing and repair activities are typically outsourced to 3rd party service companies.

Gaslift surveillance on those fields is a challenging task. Multiple global and local service companies provide solutions for gaslift optimization. One of the most common gaslift optimization surveys is logging the downhole pressure by descending a pressure gauge with help of wireline operation into the well.

In the case study presented in this thesis, the alternatives for efficient gaslift surveillance are either running flowing and static gradient surveys using conventional wireline and slickline units, or introducing intervention-less surveillance service providers. The assumed capacity of surface compressing and production facilities could handle a significant increase in production without immediate upgrade. The main constraint for achieving optimum production in the presented case, were poor gaslift metering and unknown downhole gaslift distribution.

4.6 Modeling uncertainty

Probability in decision analysis can be defined as a decision-maker's degree-of-belief about the likelihood of uncertain event. As a measure of a decision-maker's judgement or as to the likelihood of an uncertain event, probability is subjective (Brownly, 2013, p. 74). As a result of personal judgement of likelihoods, different people might give different probabilities to the same event. Probabilities that accurately reflect the uncertainties in the decision is one of the cornerstones in the decision model.

Probabilities can represent either discrete or continuous event. A discrete probability can suit objectives evaluated by constructed measures such as levels. When scoring alternatives, the decision-maker shall specify the probability the alternative scores one or another level.

The expected value in the case of discrete probabilities can be calculated by summing the product of all the levels and their discrete probabilities $EV(X) = \sum P\ (X = x)$.

When scoring alternatives evaluated by natural measures, such as costs, profits etc. A continuous probability function can be used to describe a more realistic scenario.

The procedure described in this decision model for eliciting probabilities for continuous uncertain events, is the procedure proposed by Brownly (Brownly, 2013, pp. 85-92). To address the vast number of possible outcomes Brownly proposed to focus on ranges rather than on individual possible outcomes. This procedure can suit well the uncertainty related to production gain and loss, or the uncertainty related to service cost. Nevertheless, will be used only for production gain in the initial decision model.

The first step is defining the edges of the distribution. Or the high and low values for each outcome as shown in Table 1. Direct value functions variables). The next step will be to think about all the sets of conditions, or scenarios, that would result in the actual outcome being above or below the high and low values defined in step 1. The probability of exceeding either of the levels defined in step 1 should not be greater than 1%. The third step will be determining the median of the distribution and the last step will be defining the lower and upper quartiles. This procedure will result in 5 points along the cumulative distribution function (CDF).

For continuous probability distribution for production gain achieved from gaslift surveillance survey conducted by either by intervention-based or intervention-less survey, following CDF curve can be used (Figure 29. CDF - Production gain).

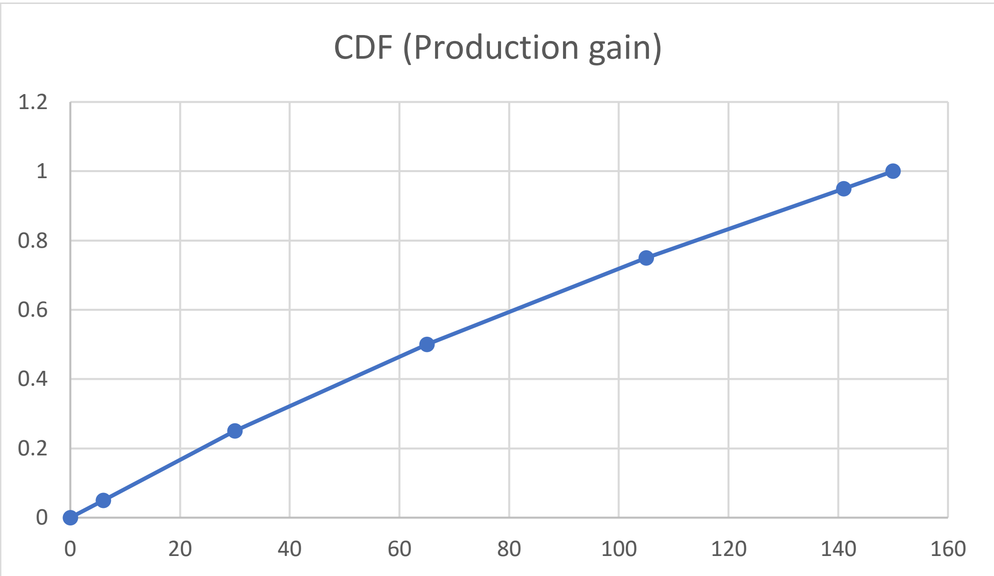


Figure 29. CDF - Production gain

The CDF function should represent the decision-maker degree of belief about the likelihood of gaining production associated with the survey. Decision maker’s assessment of the possible gain as a function of cumulative probabilities are summarized in Table 2. Production gain probability.

Prod. gain	CDF
0	0
6	0.05
30	0.25
65	0.5
105	0.75
141	0.95
150	1

Table 2. Production gain probability

The expected value in this case can be calculated by the extended Pearson-Tukey approximation (Pearson & Tukey, 1965) as shown in equation [15].

$$EV_{intervention\_based} = (0.185 * 0.05fractile) + (0.630 * 0.5fractile) + (0.185 * 0.95fractile) = 68.145 \quad [\,15\,]$$

The expected value calculated in [15] is based on CDF function constructed by evaluating possible scenario with respect to production gain. This value will be used as an input to the initial default decision model for production gain for intervention-based survey (Table 3. Direct values objective score, row 9).

The decision-maker must evaluate probabilities of outcomes from different alternatives. One can argue that the same expected value for intervention-less based survey should be lower due to up to 10% uncertainty of the downhole pressure calculation. It is difficult to evaluate the difference in gain, which is multi variable function, only by comparing the values of BHP from both alternatives. For the initial default model, we will assume reduction in $EV_{intervention\_less}$ by 10%. This will result in initial expected value for production gain for intervention-less survey of $EV_{intervention\_less} = 61.331$ (Table 3. Direct values objective score, row 2).

Probability distribution can play a significant role in the final score of the alternatives for a specific decision. Therefore, probability distribution for uncertain metrics such as production and costs should represent as realistic as possible likelihood of the results. The CDF procedure suggested by Brownly is a simple approach to construct the required probability function, based solely on general brainstorming regarding the possible outcomes. Dedicated software tools can be used to better model outcome distribution and will be used in probabilistic modeling in sensitivity analysis to test the results as a function of distribution of outcomes and preferences for all uncertain parameters.

4.7 Scoring alternatives

The alternatives identified for the decision are scored based on the preferences of the decision-maker and converted to single dimension score. Each outcome gets scored with single dimensional value $v_{obj}(x)$ based on corresponding value function (Figure 24. Production gain value function, Figure 25. Production loss value function, Figure 26. Service cost value function, Figure 27. Indirect service cost value function, Figure 28. Piecewise linear value function). The expected value $E[v_{obj}(x)]$ is calculated based on probability distribution for uncertain objectives. The input for default initial decision model presented in Table 3. Direct values objective score.

The input values for intervention-less survey used for default initial model are as follows:

- Production gain for accessible wells estimated to 0.9*EV(CDF) calculated in equation [15] = 61.331. The 0.9 factor applied as a result of reduced accuracy (+/-10%) associated with the method (Table 3. Direct values objective score, row 2).
- Production gain for restricted wells estimated to 0.5 of EV(CDF) calculated in equation [15] = 34.073. 10% of the well count is considered restricted for wireline intervention (Table 3. Direct values objective score, row 3).
- Direct survey cost estimated to 7000 $ (Table 3. Direct values objective score, row 4).
- Indirect survey cost estimated to -10000 $, considering savings in provided information for gas composition, gaslift and produced gas rates, identification of tubing leaks eliminating leak detection surveys, and opportunity to optimize wireline resources for other operations (Table 3. Direct values objective score, row 5).
- There is no downtime considered due to intervention-less nature of the survey (Table 3. Direct values objective score, row 6,7).

The input values for intervention-based survey used for default initial model are as follows:

- Production gain for accessible wells estimated to EV(CDF) calculated in equation [15] = 68.145 (Table 3. Direct values objective score, row 9).
- Production gain for restricted wells cannot be achieved for intervention-based survey, therefore is 0 (Table 3. Direct values objective score, row 10).
- Direct survey cost estimated to 8000 $ (Table 3. Direct values objective score, row 11).
- Indirect survey cost estimated to 0 $, considering no additional information or optimization opportunities of operational resources (Table 3. Direct values objective score, row 12).
- Estimated downtime of 0.04% during the survey is required for rig-up and rig-down purposes. High-rate wells must be choked to be able to run the tool downhole.
- Estimated downtime of 0.001% considered as a result of the survey, where the intervention could cause damage and the well can not produce as a result of the survey (Table 3. Direct values objective score, row 13,14).

Row	Default initial model:					
1	**Intervention-less survey**	**Objectives**	**Value** (x)	**Single Dim. Value** $v_{obj}(x)$	**Local weights**	**Expected Value** $E[v_{obj}(x)]$
2	Production gain	Accessible wells	61.331	0.838	90%	0.391
3		Restricted wells	34.073	0.587	10%	
4	Cost	Survey cost	7000	0.495	80%	0.084
5		Indirect cost	-10000	0.217	20%	
6	Downtime	During the survey	0	1.000	80%	0.200
7		Resulted by the survey	0	1.000	20%	
8	**Intervention-based survey**					
9	Production gain	Accessible wells	68.145	0.838	90%	0.377
10		Restricted wells	0	0.000	10%	
11	Cost	Survey cost	8000	0.344	80%	0.059
12		Indirect cost	0	0.217	20%	
13	Downtime	During the survey	0.040%	0.994	80%	0.199
14		Resulted by the survey	0.001%	1	20%	

Table 3. Direct values objective score

The outcomes of the scoring system are also a function of preferences of the decision maker. Like the objective hierarchy itself, the scoring system can be applied differently in each specific case. The score for each objective is further converted based on piecewise linear function (Figure 28. Piecewise linear value function) and converted to single dimensional value based on weight distribution. The weight distribution is also a function of the preferences of the decision-maker. The scores estimated by the decision-maker considered certain, hence no probabilities considered in this case.

Piecewise Linear Value Functions		**Score**			**Single dimensional value**	
Objective	**Levels**	**Intervention-based**	**Intervention-less**	**Weights**	**V(Intervention-based)**	**V(Intervention-less)**
Minimize operational risk	4 - No added operational risk 3 - Minimum operational risk 2 - Normal operational risk 1 - Excessive operational risk 0 - Operational risk must be mitigated prior execution	**2**	**3**	**30.0%**	**0.15**	**0.18**
Minimize environmental footprint	4 - No added carbon emission 3 - Minimum added carbon emission 2 - Expected amount of added carbon emission 1 - Over expected added	**2**	**3**	**25.0%**	**0.125**	**0.15**

	carbon emission 0 - Mitigation for emission is required prior to execution					
Innovation	4 - Innovative scalable technology adding IP to the company 3 - Innovative technology. Resource demanding implementation 2 - Innovative technology in R&D stage. Uncertain future IP. 1 - Standard conventional technology 0 - Old technology	**1**	**3**	**12.5%**	**0.05**	**0.075**
Increase team competence	4 - Adding highly valued competence to the team 3 - Adding competence to individuals in certain fields 2 - Adding no additional competence to the team 1 - Requires internal competent resources to implement 0 - Requires external competent resources to implement	**3**	**4**	**17.5%**	**0.105**	**0.175**
Facilitate smart digital platforms	4 - Producing large amounts of quality data on flexible platform 3 - Producing quality data on digital platform 2 - Producing data. Lack of compatibility with existing platforms 1 - Producing text report 0 - Producing no digital data	**2**	**4**	**15.0%**	**0.075**	**0.15**
Total single dimensional indirect value				**100.0%**	**0.505**	**0.73**

Table 4. Indirect values objective score

The overall score for the alternatives is derived in 4 following steps:

1. The value for each outcome is derived from the representative value function for the corresponding objective $v_{obj}(x)$.
2. Each objective score is normalized with the representative weight fraction $w_{obj} * v_{obj}(x)$. .
3. The total expected value for each fundamental value is calculated for each alternative based on equation [16] and presented in Table 3:

$$EV = w_{obj\_1} * E[v_{obj_1}(x_1)] + \ w_{obj_2} * E[v_{obj_2}(x_2)] + \cdots + w_{obj_n} * E[v_{obj_n}(x_n)] \quad [\ 16\ ]$$

4. The total score for each alternative is calculated based on weight distribution between the fundamental objectives.

$$Total\ score\ = w_{direct\_value} * EV_{direct\_value} + w_{indirect\_value} * EV_{indirect\_value}$$

[17]

The total score (Table 5. Total score initial model) is based on the input data presented in Table 3. Direct values objective score, Table 4. Indirect values objective score, and weight distribution between fundamental goals (Figure 21. Fundamental goals).

	Intervention-based	Intervention-less
Weight direct values	70%	
Weight indirect values	30%	
Total score	0.596	0.691

Table 5. Total score initial model

4.8 Sensitivity analysis

Sensitivity analysis is a valuable tool that evaluates the impact of various sources or input values on a specific dependent variable within a set of assumptions or theories. Its primary purpose is to explore how different sources of uncertainty in a mathematical model affect its overall uncertainty.
In the model presented in the previous section, the only uncertain parameter considered was the production gain. The probability distribution of this parameter was assessed by constructing a cumulative distribution function (CDF) based on possible outcomes concerning the potential gain in production. However, this approach does not account for the impact of other uncertain parameters that could affect the model's overall uncertainty. Other parameters such as direct and indirect costs, downtime, and weight distribution can also contribute to uncertain outcomes and influence the alternatives' scores. To investigate the sensitivity of the decision model to the distribution of outcomes and its impact on the overall score, a Montecarlo simulation is utilized. Table below (Table 6. Montecarlo input table) presents a summary of the outcomes for the uncertain parameters, which were used as inputs in the Montecarlo simulation.

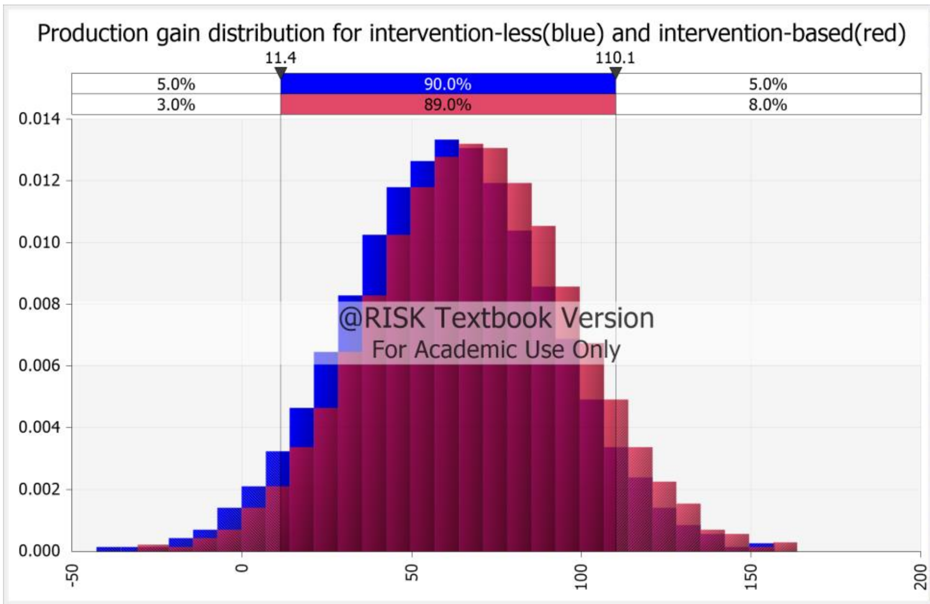
Intervention-less	Distribution	Value	Expected Single Dim. Value	Local weights	Norm. Value
Production gain accessible	RiskNormal(61,30)	61	0.801	0.9	0.381
Production gain restricted	RiskNormal(20,10)	20	0.403	0.1	
Direct cost	RiskPert(4000,7000,12000)	7333	0.439	0.8	0.075
Indirect cost	RiskJohnsonSU(2,2,1,10000)	-13316	0.246	0.2	

Downtime during survey	0	0	1.000	0.8	0.199
Downtime due to survey	RiskPareto2(0.05,20)	0	0.972	0.2	
Intervention-based					
Production gain accessible	RiskNormal(68,30)	68	0.837	0.9	0.377
Production gain restricted	0	0	0.000	0.1	
Direct cost	RiskPert(4000,8000,13000)	8167	0.324	0.8	0.054
Indirect cost	RiskPearson6(2,2,1000)	2000	0.113	0.2	
Downtime during survey	RiskPareto(7,0.04)	0.047	0.513	0.8	0.117
Downtime due to survey	RiskPareto2(0.05,10)	0	0.867	0.2	
Weight fraction direct values	RiskVary(0.7,0.5,1,2,5, "Uniform",RiskStatic(0.7))	0.7			
Weight fraction indirect values	$1 - W\_direct$	0.3			
	Intervention-based	**Intervention-less**			
Total score	0.512	0.649			

Table 6. Montecarlo input table

4.8.1 Distribution models of uncertain parameters

In the decision-model constructed in this chapter, the production gain for accessible wells is described using a normal distribution. However, it should be noted that the intervention-less survey used to determine the bottom-hole flowing pressure (BHFP) is less accurate than a intervention-based wire line survey. As a result, assumption is made that the distribution of the production gain is shifted towards a lower mean value (Figure 30. Production gain distribution). This implies that the estimation of BHFP via intervention-less survey has an impact on the overall production gain of the well. The lower accuracy of the survey results in a reduction in the estimated production gain, which in turn affects the overall well performance assessment.
This assessment is particularly relevant to engineers who utilize bottom-hole flowing pressure (BHFP) as the primary parameter for production optimization of gas-lifted wells. It should be noted that there exist multiple approaches to optimize gaslift performance, such as constructing gaslift performance curves (GLPC), evaluating downhole valves efficiency, and optimizing surface choke settings. The choice of optimization approach can have an impact on the uncertainty assessment related to production gain. The decision-maker must consider the circumstances surrounding the parameter when evaluating possible outcomes.



Statistics

	RiskNormal(61,30) ...	RiskNormal(68,30) ...
Cell	Sheet42!D34	Sheet42!D42
Minimum	-42.87	-30.70
Maximum	157.03	163.65
Mean	60.99	68.00
90% CI	± 1.562	± 1.562
Mode	56.09	60.02
Median	60.93	67.94
Std Dev	30.01	30.00
Skewness	-0.0065	-0.0022
Kurtosis	2.9932	2.9791
Values	1000	1000
Errors	0	0
Filtered	0	0
Left X	11.4	11.4
Left P	5.0%	3.0%
Right X	110.1	110.1
Right P	95.0%	92.0%
Dif. X	98.72	98.72
Dif. P	90.0%	89.0%
1%	-9.43	-1.83
2.5%	2.18	8.88
5%	11.39	18.61
10%	22.51	29.41
20%	35.68	42.67
25%	40.71	47.67
30%	45.23	52.21
35%	49.37	56.43
40%	53.38	60.33
45%	57.17	64.21
50%	60.93	67.94
55%	64.72	71.76

Figure 30. Production gain distribution

Restricted wells cannot be surveyed by intervention-based technics due to restrictions in the production tubing preventing the tool from getting to target depth. The presence of downhole restrictions also hinders the exchange of gas-lifted valves for redesign purposes. This limitation may have implications for the accuracy of the optimization process, as it may result in suboptimal production gains compared to wells where gas-lifted valves can be modified.

Intervention-less surveys have no limitation with respect to tubing restrictions and can be executed even in wells not accessible by wireline. Provided that there is a continuous flow of lift gas, the tracer gas injected at the surface will be transported downhole by the lift gas. Once the tracer mixes with the produced fluids, it will rise to the surface and provide the required fingerprint for calculation of downhole gaslift rate and distribution.

When restricted well is surveyed by intervention-less method, the optimization can be performed by adjusting the gaslift rate to its optimum value and optimizing surface choke settings. Considering this limitation, the estimated value from optimizing restricted wells from intervention-less survey is distributed normally but expected to be lower than optimizing accessible wells (Figure 31. Production gain from restricted wells).

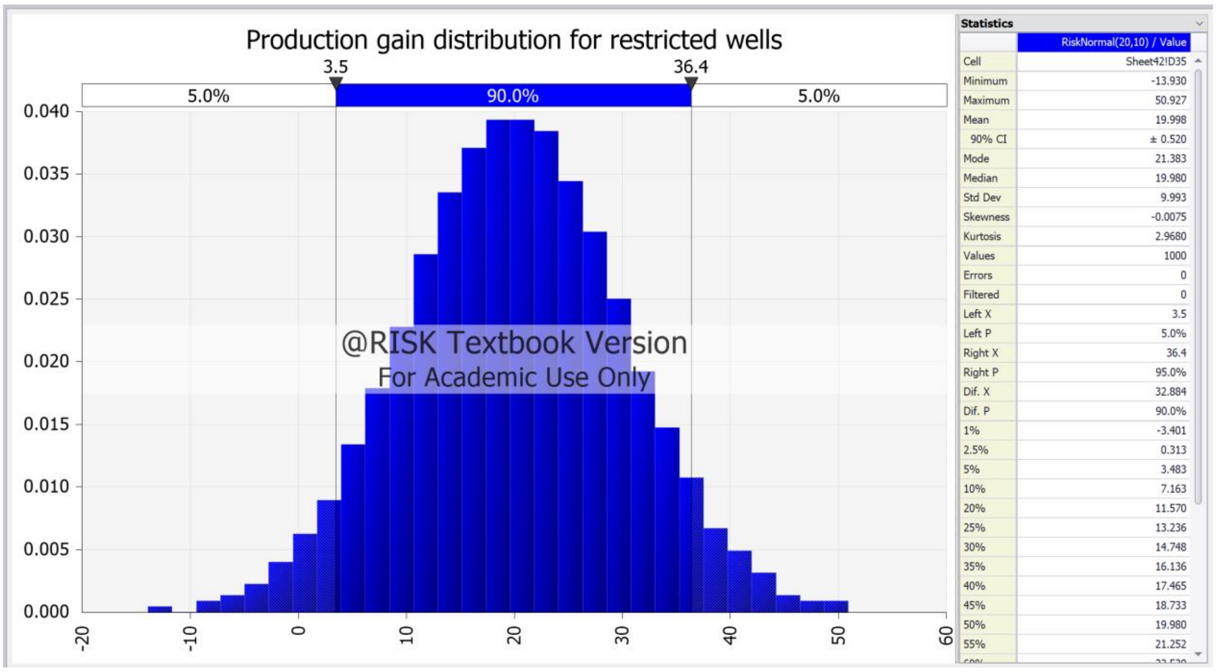


Figure 31. Production gain from restricted wells

The budgetary cost-estimates for the surveys are typically known or can be provided by the vendors, but can vary depending on source, scope of work, and contractual terms and conditions. Direct costs can be described by PERT distribution. Which is continuous distribution bounded on both sides. The estimated mean cost for intervention-less survey is 7000 USD, while the estimated mean cost for intervention-based survey is 8000 USD (Figure 32. Direct cost distribution).

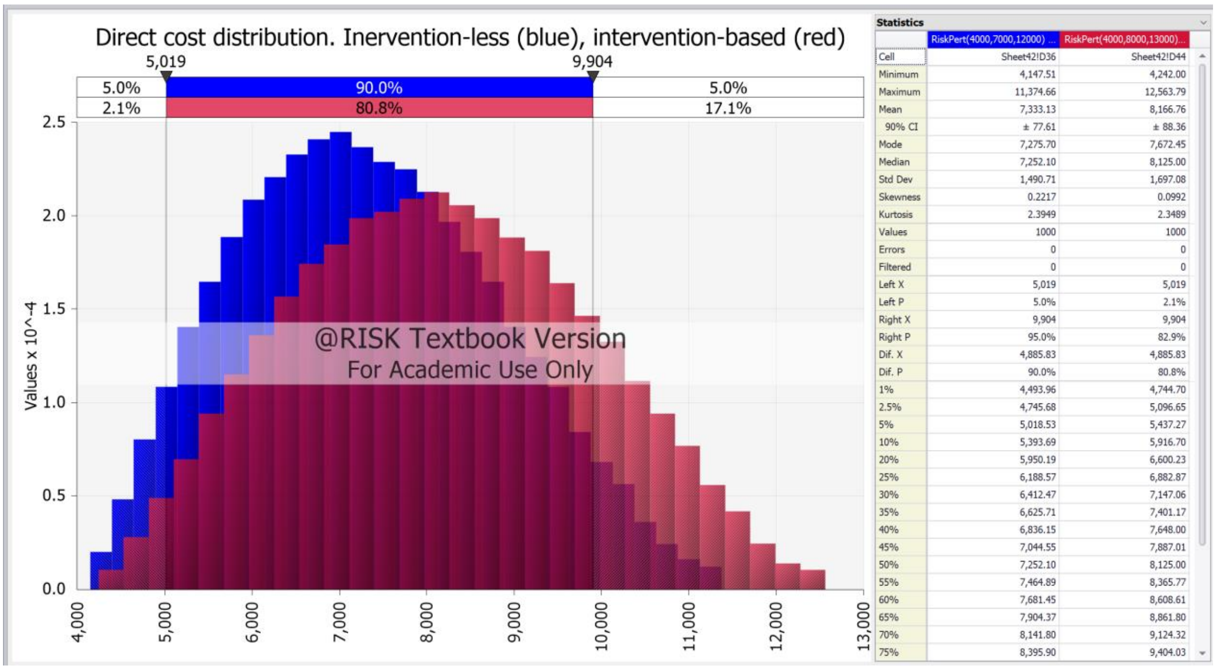


Figure 32. Direct cost distribution

Indirect costs refer to costs and savings indirectly associated with the survey. Savings can be generated by either providing additional data that otherwise would generate direct costs or by optimizing the use of other operational resources. Data such as gas composition can eliminate the need for external compositional analysis, Data for gaslift and produced gas rates can eliminate the need for flow metering, and identification of tubing leaks can reduce the need for leak detection surveys. Utilization of one or the other practice can create opportunities to optimize resources for other operations.

One also should consider the data generated by one or the other survey provider. When data collected during the survey does not align with a company's existing systems, there may be costs associated with converting and importing the data into those systems. These costs can be associated with the need for specialized software or hardware, additional personnel, or other resources to manage the data integration process. The time required to analyze the data and interpret the results can also affect the efficiency of optimization activities.

When a company is converting its wells to gaslift and will require an increase in utilized resources, it is important to consider the scaling potential of the service. This involves assessing the ability of the gaslift service to accommodate the increased demand for resources without compromising its performance or quality. Factors such as the availability of personnel and equipment, should be evaluated to ensure that the gaslift service can effectively meet the needs of the company's expanding operations.

Indirect costs, that may result from the survey, are costs associated with workover, fishing operations or any other work that requires production stop. The survey can also contribute to operational bottlenecks that can result in delays with respect to bringing the wells online, and unexpected shutdowns.

The use of internal resources should also be considered. Utilization of 3rd party services may generate in-kind costs for the company.

Intervention-less survey provides a valuable set of additional data and can result in indirect savings, while intervention-based survey carries operational risk and can be translated to indirect costs (Figure 33. Indirect costs distribution).

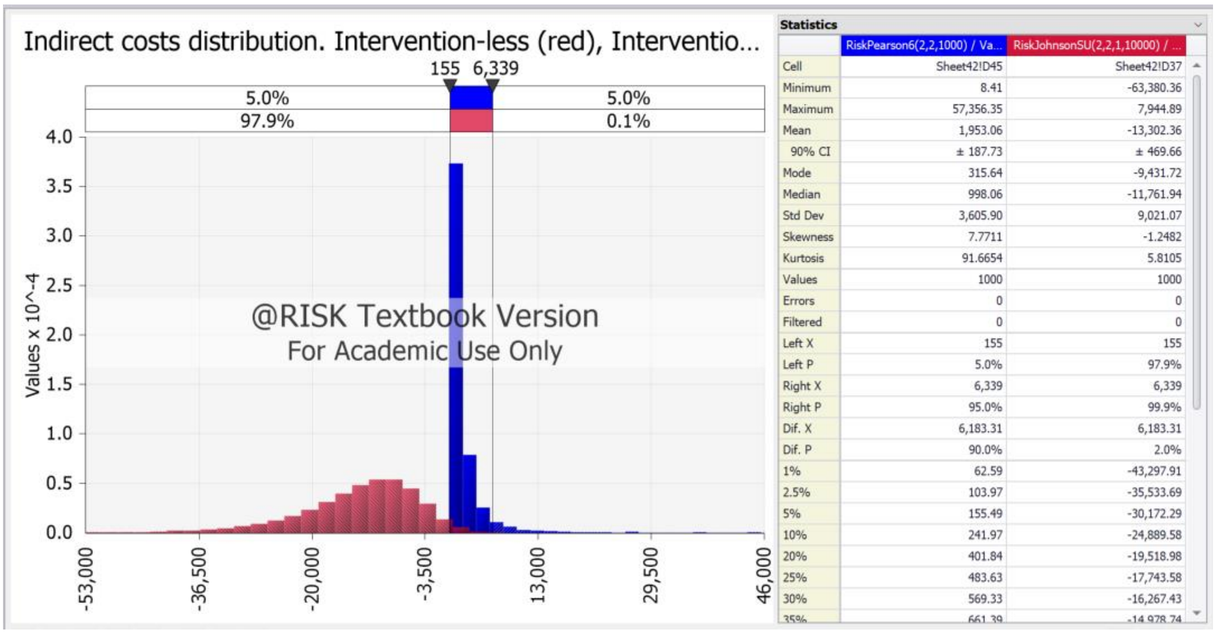


Figure 33. Indirect costs distribution

Considering the downtime associated with rigging the tools for survey execution, it is important to note that the intervention-based approach requires shutting in the well. This can result in an average shut-in duration of approximately one hour (0.04 day). However, the actual duration of the shutdown can vary depending on factors such as the experience of the crew, the mechanical condition of the well, and the required equipment. These uncertainties are described by a Pareto distribution (as shown in Figure 34 for downtime during rigging). In contrast, no shut-in is required to rig up the equipment for an intervention-less survey. The equipment can be connected to existing connection points on the wellhead without any disturbance to the well's production, reducing the potential for downtime and associated costs.

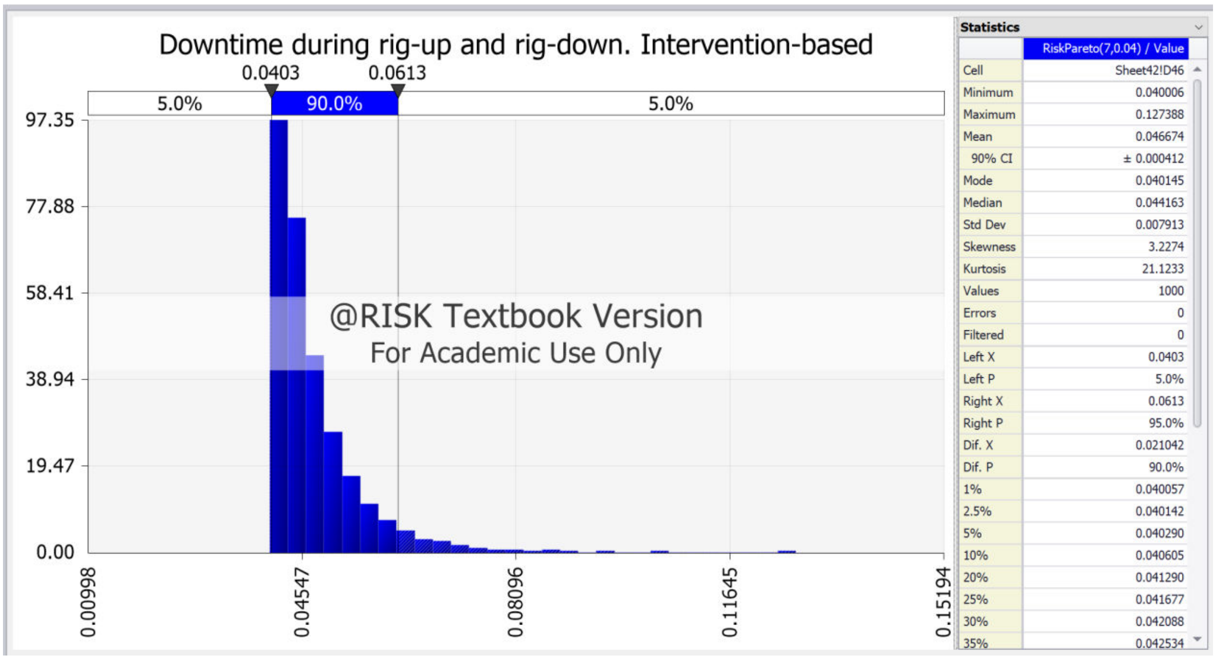
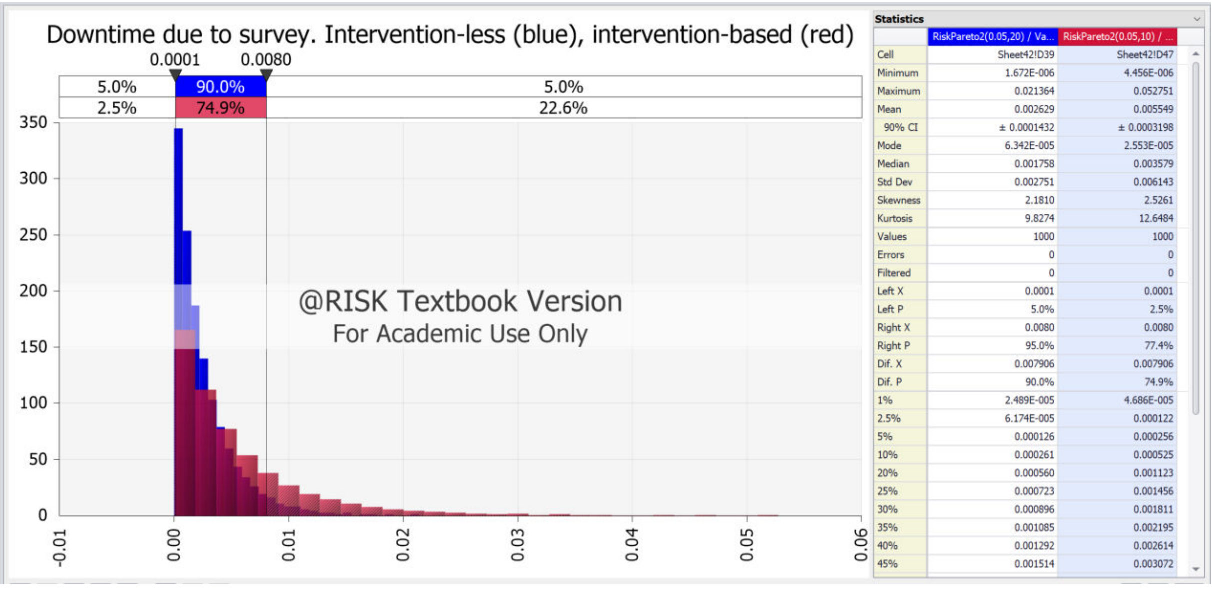


Figure 34. Downtime during rigging

Another implication is when the well cannot be produced as a result of the survey itself. For example, stuck tools downhole or mechanical damage to the wells preventing those from aligning back online. Downtime resulted by the survey is defined with Pareto2 distribution, which describes the probability of downtime fraction. The probability of such an event may be low, but the consequences are significant. Damages caused during gaslift surveillance survey may compromise wells safety. Repair or fishing operation may be required to return the well to normal production. In the case of intervention-based survey, one can assume higher risk of damage due to the nature of intervention. Intervention-less surveys, on the other hand, carry minimum operational risk, hence result in lower probability to damage the well during the survey (Figure 35. Downtime due to survey).



Statistics

	RiskPareto2(0.05,20) / Va...	RiskPareto2(0.05,10) / ...
Cell	Sheet42!D39	Sheet42!D47
Minimum	1.672E-006	4.456E-006
Maximum	0.021364	0.052751
Mean	0.002629	0.005549
90% CI	± 0.0001432	± 0.0003198
Mode	6.342E-005	2.553E-005
Median	0.001758	0.003579
Std Dev	0.002751	0.006143
Skewness	2.1810	2.5261
Kurtosis	9.8274	12.6484
Values	1000	1000
Errors	0	0
Filtered	0	0
Left X	0.0001	0.0001
Left P	5.0%	2.5%
Right X	0.0080	0.0080
Right P	95.0%	77.4%
Dif. X	0.007906	0.007906
Dif. P	90.0%	74.9%
1%	2.489E-005	4.686E-005
2.5%	6.174E-005	0.000122
5%	0.000126	0.000256
10%	0.000261	0.000525
20%	0.000560	0.001123
25%	0.000723	0.001456
30%	0.000896	0.001811
35%	0.001085	0.002195
40%	0.001292	0.002614
45%	0.001514	0.003072

Figure 35. Downtime due to survey

The weight distribution between direct and indirect values described in Figure 21. Fundamental goals), can also have an impact on the final score of the alternatives. In the decision-model presented in this chapter, the direct values representing maximizing NPV from operational expenditures (OPEX) being weighted to 0.7, while indirect values representing maximizing company's image and IP to 0.3. In order to test the sensitivity of the model to this input, we will define it as Vary distribution from 0.5 to 1 (Figure 36. Weight distribution for fundamental objectives).

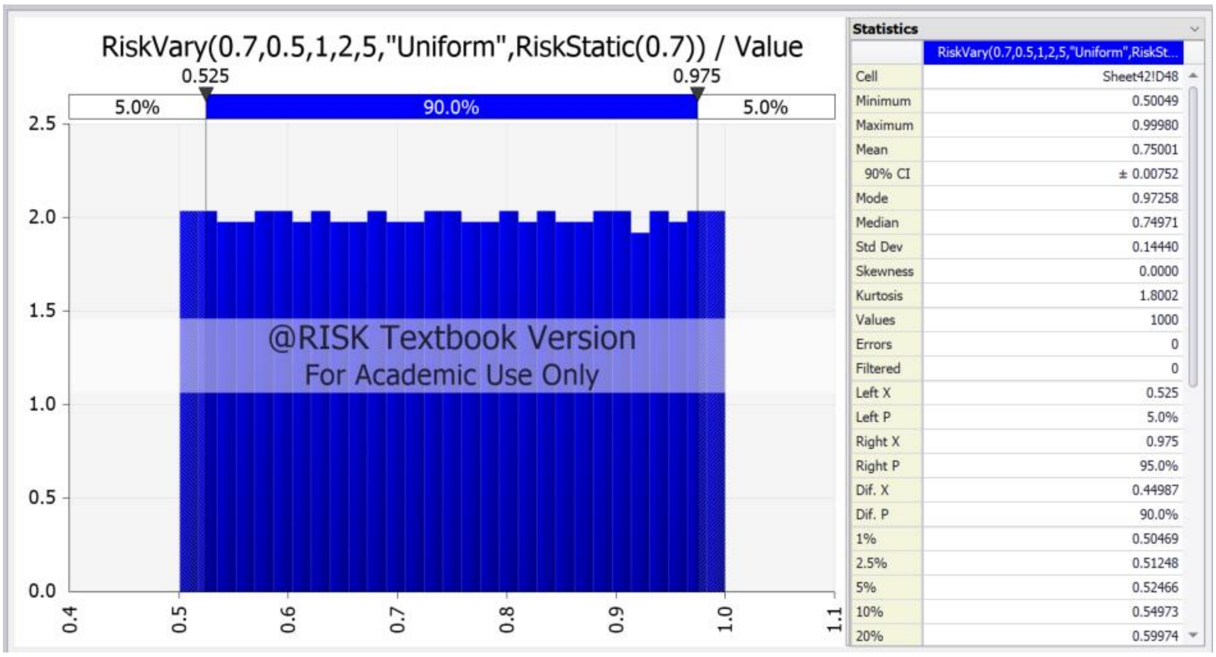


Figure 36. Weight distribution for fundamental objectives

The weight distribution between accessible and restricted wells is also described by Vary distribution ranging from 0.7 to 1 for accessible wells (Figure 37. Weight distribution for accessible wells).

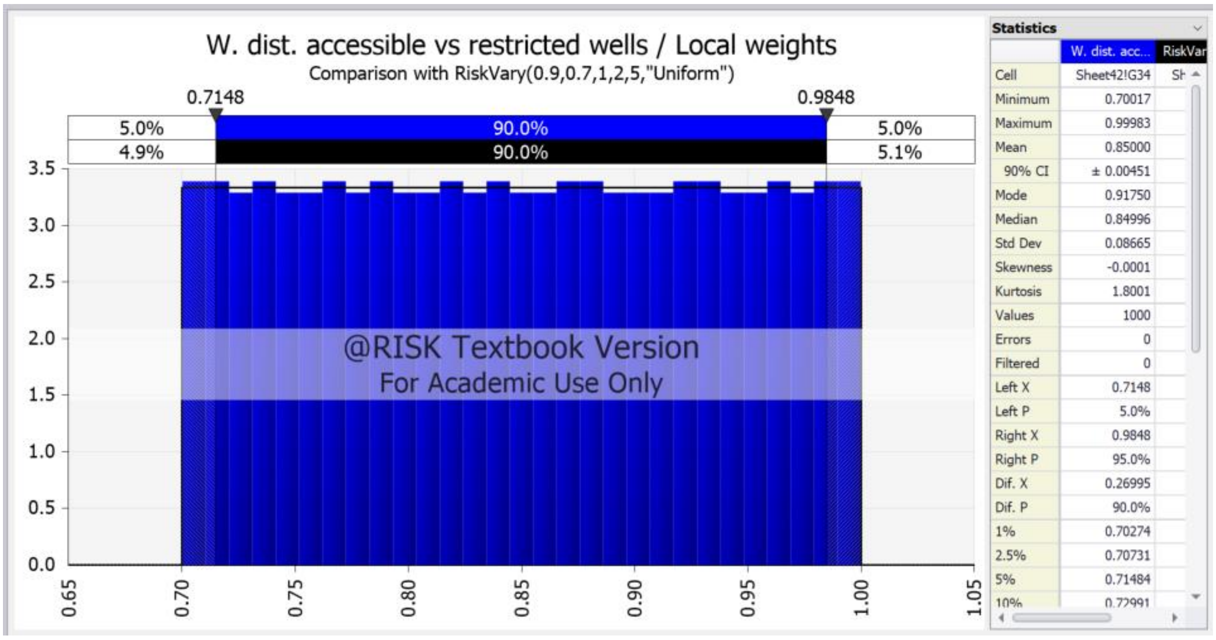


Figure 37. Weight distribution for accessible wells

4.8.2 Monte Carlo Simulation

Monte Carlo simulation is a computational method involving random sampling to obtain numerical results. The simulation can be used to estimate the probability distribution of a model's outputs based on distribution of uncertain input parameters. In the context of the presented decision model, we want to test the sensitivity of the total score for each alternative to change in input parameters such as production gain, direct and indirect costs, down-time, and weigh distribution of fundamental objectives. The model is run for each input scenario, and the resulting output values are presented below. The collected data can be used to study various statistical measures of the output distribution and to evaluate the effects of input parameter uncertainties on the model.

Running Monte Carlo simulation using the probability distributions defined for each of the uncertain outcomes (Table 6. Montecarlo input table), we can study the results for each of the alternatives studied in the decision model.

4.8.2.1 Intervention-based Monte Carlo results

The distribution of the results from Monte Carlo simulation for intervention-based survey presented in Figure 38. Monte Carlo Intervention-based results. Simulated distribution of the total score has a range of 0.050 to 0.698, with a mean of 0.512. The data is tightly distributed, with 90% of the values falling within a narrow interval of ± 0.004 around the mean. The mode of the distribution is 0.534, which is slightly higher than the median of 0.520, indicating a slight positive skewness. The standard deviation of the distribution is 0.077, indicating that the data has relatively low dispersion. The skewness of -1.394 indicates that the distribution is left-skewed, with more low values and fewer high values. The kurtosis of 7.785 indicates that the distribution is leptokurtic, which means it has a sharp peak and heavy tails compared to a normal distribution.

According to the results of the initial model (Table 5. Total score initial model), which was primarily deterministic, the score for intervention-based surveillance is 0.596. This score is slightly higher than the mean score of 0.512 obtained from Monte Carlo simulation. These findings suggest that utilizing probability distributions of outcomes led to a lower overall score for intervention-based surveillance.

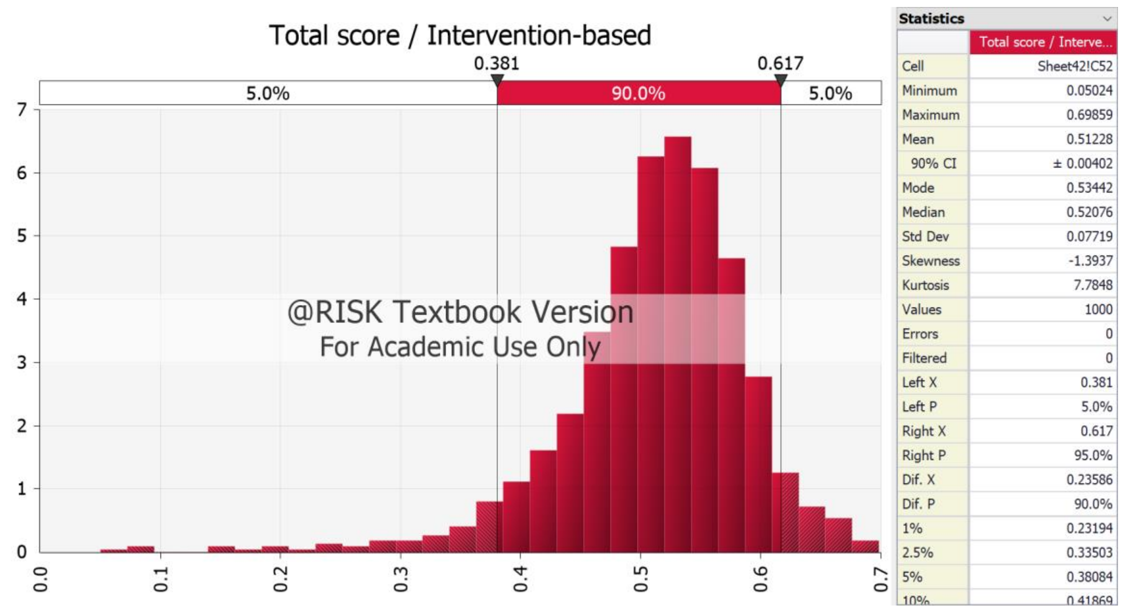


Figure 38. Monte Carlo Intervention-based results

The tornado graph (Figure 39. Tornado. Intervention-based results) ranks inputs to the model by effect on output mean. The results indicate that the parameter of production gain on accessible wells has the most significant impact on the total score/output. This correlates with the corresponding weight value in the decision model (Table 1. Direct value functions variables). The distribution of production gain in accessible wells has a considerable impact on the range of output, with values ranging from 0.362 to 0.571. Although production gain input is distributed normally, low input values have a larger negative effect on the total score compared to high input values. This is due to the concavity of the value function (Figure 24. Production gain value function) used to describe the value obtained from the possible gain.

The range of output associated with direct costs is 0.485 to 0.572, while indirect costs result in a lower output range of 0.502 to 0.524. The convexity of corresponding value function (Figure 26. Service cost value function) results in higher positive effect of low input on overall score.

Weight distribution between accessible and restricted wells also has a significant effect on overall score. This is due to the inherent limitation of intervention-based methods to survey restricted wells. Higher weight allocation of restricted wells reduces the overall score for this alternative. The range of output resulted by the simulation in this case is 0.472 to 0.550.

Input parameters related to downtime, indirect costs and weight distribution for fundamental goals have lower impact on overall score and range from approximately 0.50 to 0.52.

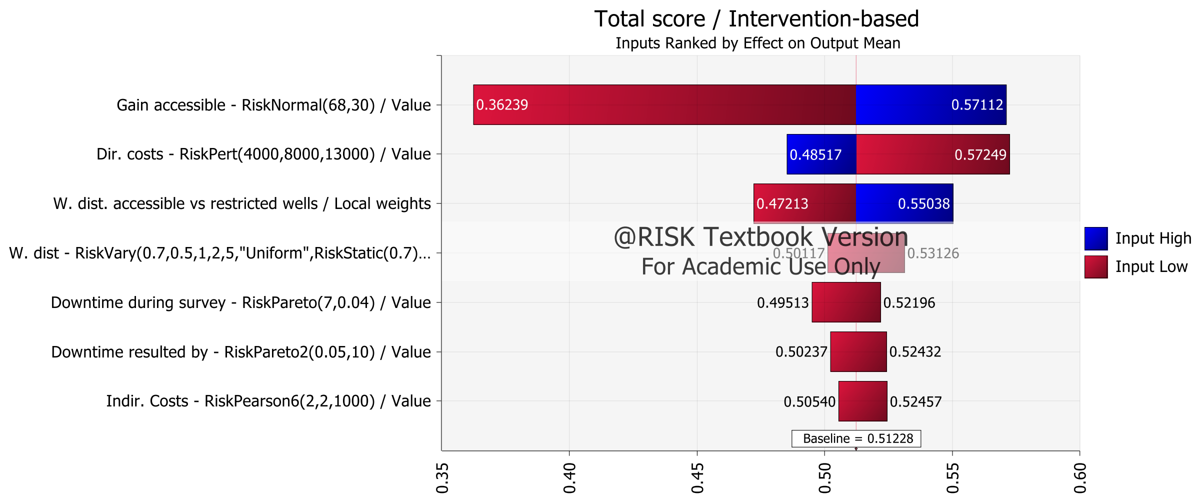


Figure 39. Tornado. Intervention-based results

The correlation coefficients illustrated in Figure 40. Correlation coefficients for intervention-based simulation, measure the strength and direction of the relationship between variables.

Input values for production gain for accessible wells, correlate positively with overall score. This consistent with the increasing value function for production gain, constructed for the decision model (Figure 24. Production gain value function).

The fraction of accessible wells also correlates positively with the overall score. Considering the limitation with respect to intervention to restricted well, the value increases with increased number of accessible wells.

Moreover, increasing weight allocation to direct values such as maximizing NPV from operational expenditures (OPEX) has a positive correlation with the overall score. The intervention-based score for company image and IP, calculated by piecewise linear value functions, (Table 4. Indirect values objective score), is significantly lower than the intervention-less one. Therefore, a decrease in the weight allocation for that parameter results in a better overall score.

The result is negatively correlated with direct costs and downtime, whereas there is no measured correlation with indirect costs.

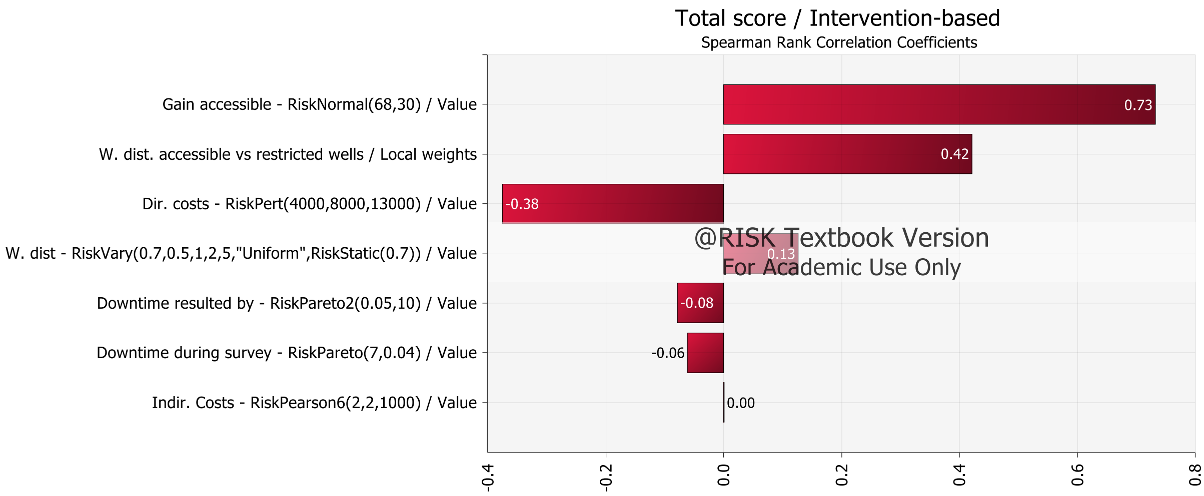


Figure 40. Correlation coefficients for intervention-based simulation

4.8.2.2 Intervention-less Monte Carlo results

The distribution of the results from Monte Carlo simulation for intervention-less survey presented in Figure 41. Monte Carlo Intervention-less results. The range of the total score is from -0.074 to 0.834, with a mean of 0.649. The mode and median values of 0.683 and 0.666, respectively, are relatively close to the mean, which may indicate that the draft distribution is approximately symmetric. However, the negative skewness value of -2.279 suggests that there may be more extreme values on the lower end of this distribution. The standard deviation value of 0.089 indicates that there is a moderate amount of variability in the data. The high kurtosis of 13.213 indicates that the distribution has a sharp peak and heavy tails compared to a normal distribution.

According to the results of the initial model (Table 5. Total score initial model), the score for intervention-less surveillance is 0.691. This score is slightly higher than the mean score of 0.649 obtained from Monte Carlo simulation. The results show that incorporating probability distributions to model outcomes resulted in a lower overall score for intervention-less surveillance.

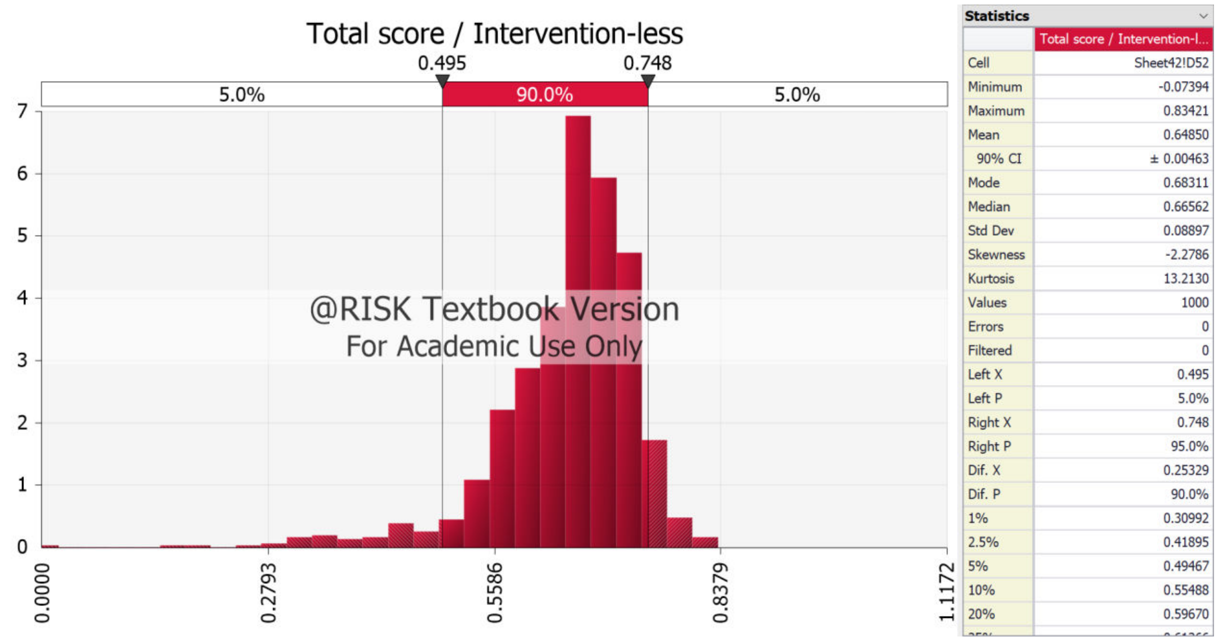


Figure 41. Monte Carlo Intervention-less results

The tornado graph (Figure 42. Tornado. Intervention-less results) indicates that the parameter of production gain on accessible wells has again the most significant impact on the total score. This due to the corresponding high weight-fraction allocated to this parameter in the decision model (Table 1. Direct value functions variables). The distribution of production gain in accessible wells has a considerable impact on the range of output, with values ranging from 0.470 to 0.714. The results show that low input values have a larger negative impact on the total score than high input values. This can be attributed to the concavity of the value function depicted in Figure 24. Production gain value function) used to describe the value obtained from the possible gain.

The range of output associated with direct costs is 0.611 to 0.711, while indirect costs result in a lower output range of 0.631 to 0.664. The convexity of corresponding value function (Figure 26. Service cost value function) contributes to higher positive effect of low input on overall score. The range of the latter is slightly higher than the range resulted in intervention-based simulation. This is due to higher possible saving incorporated into intervention-less surveillance.

Weight distribution between direct and indirect values of fundamental goals has a moderate effect on overall score, ranging from 0.625 to 0.677. The score for indirect values, calculated by piecewise linear value functions, results in a higher overall score when the relative weight-fraction of direct values reduces.

Weight distribution between accessible and restricted wells on the other hand, has a less significant effect on overall score compared to intervention-based surveillance. This is due to the ability of intervention-less methods to survey restricted wells. However, higher weight allocation of restricted wells still reduces the overall score. This is a result of optimization practice of optimizing the gaslift injection rate only, without the possibility of improving the operating point. The estimated gain from this approach is lower than from accessible wells. The range of output resulted by the simulation in this case is 0.632 to 0.676.

Lastly, the range of output for production gain from restricted wells is from 0.641 to 0.666, while the range of output for downtime resulted by the survey is from 0.634 to 0.657.

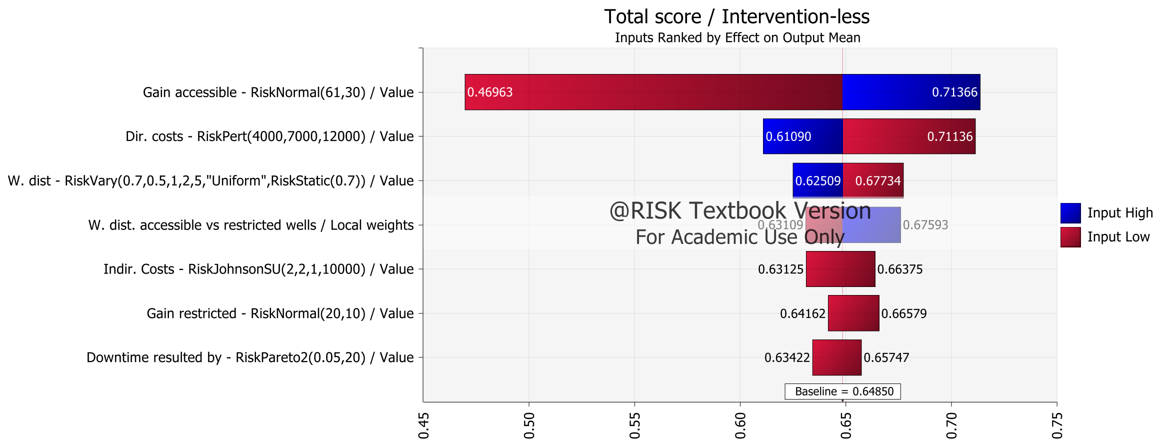


Figure 42. Tornado. Intervention-less results

The correlation coefficients for intervention-less surveillance are illustrated in Figure 43. Correlation coefficients for intervention-less simulation.

Input values for production gain for accessible wells, similarly to intervention-based results, correlate positively with overall score. Weight allocation for accessible and restricted wells also correlates positively with the results, although the effect is less significant in intervention-less approach due to the ability to survey restricted wells.

Weight distribution between direct and indirect values has a negative relationship to the results in country to intervention-based survey. This is due to elevated score given to the indirect values for intervention-less method.

Production gain from restricted wells and indirect costs have respective correlation coefficients of 0.05 and -0.02.

Downtime resulted by intervention-less survey is negligible due to reduced operational risk associated with the execution.

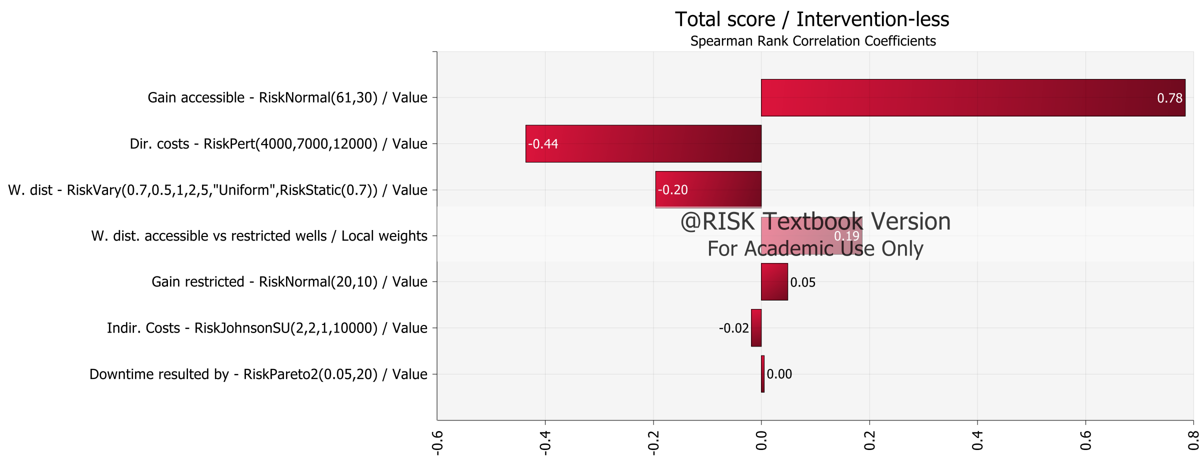


Figure 43. Correlation coefficients for intervention-less simulation

5. Discussion of the results

The topic of this thesis was decision analysis in the context of gaslift surveillance on aging brownfields. Decision analysis theory was coupled with technical evaluation of available methods.

Aging gas-lifted fields rely primarily on intervention-based services for collection of the core fundamental data required to make informed optimization decisions. Alternative methods, such as intervention-less surveillance, are rarely implemented. Lack of awareness for such alternatives or doubt about their accuracy, combined with inadequate decision-making processes, prevents the decision-makers from evaluating the objectives on a common scale and identifying potential tradeoffs for conventional assumptions.

To fully grasp the value of decision analysis, it is essential to recognize that the only way to consistently generate more value is by making better decisions. In complex and uncertain environments, humans are not inherently equipped with intuitive decision-making abilities, and should instead supplement their experience with a consistent, structured approach to decision-making, such as developing proficiency in decision analysis.

The decision model presented in this thesis was built based on MODA framework. The focus was not to identify new alternatives, but to develop suitable value functions and effective evaluation measures to score the identified objectives by normalized single-dimensional values resulting in total score for each alternative.

The total score can get any value in range from zero to one, and higher numbers are preferred. One way to interpret the total score is to reflect on the way in which the score is calculated, and the meaning of the maximum and minimum possible values. The single-dimensional value functions are weighted and normalized to arrive at the total score of the alternatives. Given how the score is calculated, a value of 1.0 reflects an alternative that is associated with the best possible consequences on all of the objectives. On a country, an overall score of 0.0 reflects an alternative that is associated with the worst possible consequences. Therefore, the score can be interpreted as the amount of value a decision maker derives from a given alternative, relative to best possible outcome.

The results of the decision model constructed in this thesis are in favor of intervention-less gaslift surveillance alternative (Table 7. Total score summary).

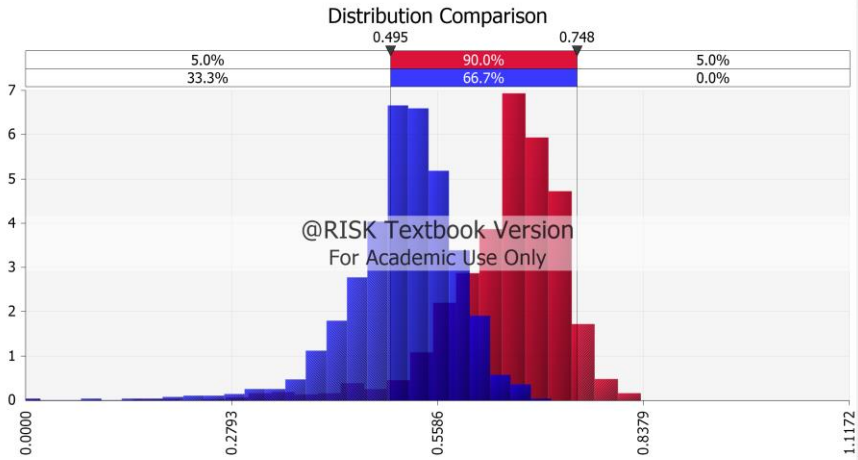
	Intervention-based	**Intervention-less**
Initial model total score	0.596	0.691
Probabilistic/Monte Carlo total score	0.512	0.649

Table 7. Total score summary

The total score for intervention-less surveillance is 16% higher considering the initial deterministic model, while the mean result from probabilistic model is 27% higher. This indicates that by introducing probabilities for the outcomes of measured objectives, strengthening the score even more in favor of intervention-less approach. Given the uncertain nature of outcomes with respect to gains, costs, and downtime for each alternative, one may assume that probabilistic modeling results in a more realistic scenario.

Comparing the range of the total score from probabilistic decision model, one can further examine the possible outcomes (Figure 44. Total score distribution comparison). While the peak values are clearly separated, the positive tail for intervention-based survey overlaps with the negative tail of the intervention-less approach. Statistically, when the positive tail of one distribution overlaps with the negative tail of the other distribution, it indicates that there is some degree of similarity or commonality between the two distributions. This reflects the similarity of the alternatives with respect to their measured outcomes. If two alternatives overlap in the context of a decision analysis, it means that there is a certain degree of uncertainty or ambiguity in choosing between them.

The size of this overlap is a function of the distributions of the 7 uncertain parameters used in the model. If the decision-maker will reduce the number of those, by eliminating the uncertainties related to survey costs, fraction of restricted wells, and the weight distribution between the fundamental values, the overlapping region may shorten, and this uncertainty will decrease.



Statistics

	Total score / Intervention-less	Total score / Intervention-based
Cell	Sheet42!D52	Sheet42!C52
Minimum	-0.07394	-0.09206
Maximum	0.83421	0.71284
Mean	0.64850	0.51154
90% CI	± 0.00463	± 0.00402
Mode	0.68311	0.50048
Median	0.66562	0.51887
Std Dev	0.08897	0.07727
Skewness	-2.2786	-1.6600
Kurtosis	13.2130	10.6300
Values	1000	1000
Errors	0	0
Filtered	0	0
Left X	0.495	0.495
Left P	5.0%	33.3%
Right X	0.748	0.748
Right P	95.0%	100.0%
Dif. X	0.25329	0.25329
Dif. P	90.0%	66.7%
1%	0.30992	0.23929
2.5%	0.41895	0.32511
5%	0.49467	0.38591
10%	0.55488	0.42554
20%	0.59670	0.46166
25%	0.61366	0.47806
30%	0.62927	0.48819
35%	0.64177	0.49798
40%	0.65082	0.50516

Figure 44. Total score distribution comparison

Cumulative distribution functions illustrated in Figure 45. Total score CDF, allow clear visualization of the results. Analyzing the CDF curves for intervention-based survey (blue) and intervention-less survey (red), one can gain clear insights into the probability of the possible score for each alternative.

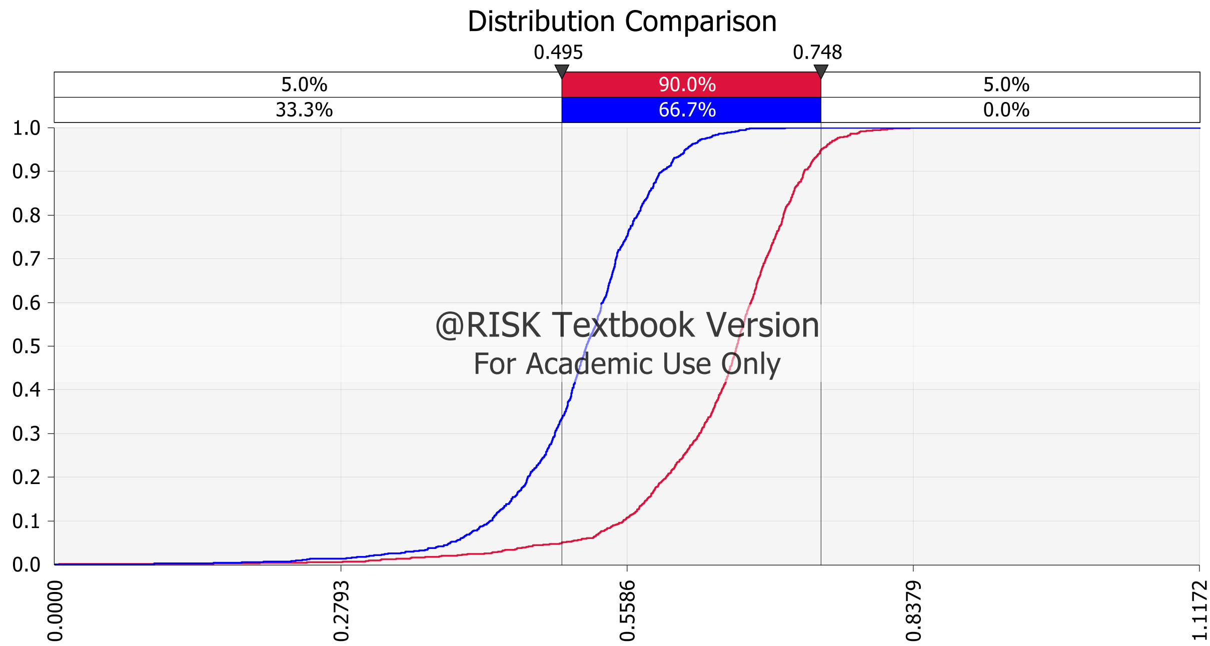


Figure 45. Total score CDF

To assess the quality of presented decision, as outlined in the decision analysis theory chapter (Decision quality), it is necessary to evaluate the following aspects:

1. Appropriate frame
2. Creative alternatives
3. Relevant and reliable information
4. Clear values and tradeoffs
5. Sound reasoning
6. Commitment to action

The context of the decision with respect to gaslift optimization of aging brownfields is thoroughly covered, and serves as a frame which outlines the challenge and opportunity including the decision to be made.

The alternatives for gaslift surveillance on aging fields are limited and often rely solely on intervention-based gradient surveys performed with help of wireline operation. Identifying additional alternative such as intervention-less survey, provides opportunity for further value creation through structured decision-making process. Although decision quality typically increases with an increasing number of relevant alternatives, in the context of aging fields, the inherent limitation of available gaslift surveillance techniques restricts the number of available options.

Relevant and reliable information required to better assess the probability distribution of possible outcomes for measured objectives. Outcomes related to gains, costs and downtime would typically be assessed based on previous operational experience. When this information is not available, field trial can provide required data and evaluate possible outcomes. In the case-study presented in this thesis, the results were indeed evaluated in a field trial (Cornwall, Shkorin, Guzman, & El-Majzoub, 2021) to better understand the ability of the available alternatives to satisfy the objective hierarchy. This approach has clearly improved the quality of the decision by enhancing the reliability of required information.

Applying MODA framework to the decision-making process, we separated the analysis of uncertainty from the analysis of preferences. This provided clarity in the evaluation of the objectives, allowing constructed evaluation measures to facilitate tradeoffs between all objectives on a common scale.

The importance of creating objective hierarchy, describing fundamental goals as a function of lower-level measurable objectives, was also thoroughly discussed in the theory and the decision model chapters.

The decision process presented in this thesis requires logical and rational thinking, or so-called sound reasoning. Sound reasoning also involves being aware of potential biases and limitations related to decision-making. Analytical features of the constructed decision were presented in detail, while organizational complexity was not addressed. Addressing organizational complexity during decision-making process, involves engaging appropriate individuals in the right manner. Decisions can vary widely from a single decision-maker with similar stakeholders, to multiple decision-makers requiring consensus from diverse stakeholders with different views. Decision-makers may not always be rational due to conflicting goals within the organization and time pressures. MODA framework can play a crucial role in bridging this gap.

Lastly, reasoning provides clarity of intention, a true decision requires action, so commitment to implement the decision is a key component. In the drafted case, the decision was made to implement intervention-less survey as a primary practice for gaslift surveillance. This again strengthens the quality of this decision.

In the conclusion chapter of the referenced SPE-208003-MS paper (Cornwall, Shkorin, Guzman, & El-Majzoub, 2021), the decision-maker Rachelle Christine Cornwall summarizes as follows. “In the current environment with increased focus on well integrity and HSE in GL operations, and the need for improved surveillance mechanisms, an innovative approach combining several methodologies to improve well performance visibility and reduce HSE impact - is the new frontier. The WITSS system provides a platform for enhancing the quality and quantity of data for granular well diagnostics. The method supports the consolidation of metering and monitoring activities without negative production impact for proactive surveillance.”

The total score (Table 7. Total score summary) provides clear answer on which alternative suits best the identified objectives, while the MODA framework, guiding the decision-making process, improves the quality of the decision.

The constructed decision analysis model showed that intervention-less surveillance is the preferable choice considering gaslift optimization activities on aging brownfields. The impact of uncertain outcomes on the overall score was assessed through sensitivity analysis, using distribution functions that were carefully adjusted to reflect the level of uncertainty.

6. Conclusion

This thesis focuses on exploring relevant elements and the framework for the decision-making process considering production optimization on aging gas-lifted fields. The decision analysis framework tailored for selecting between gaslift surveillance services, however the methodology and concept can be utilized in any other industry. The Thesis demonstrates the process developing decision analysis model for a decision with multiple objectives. Some of the key points are following:

- Professionals need a systematic methodology to make and justify better decisions
- Multi-Objective Decision Analysis (MODA) process promotes clear thinking and leads to comprehension and insights that wouldn't be apparent from intuitive process
- The framework allows to compare alternatives by weighted evaluation measures that satisfy multiple objective hierarchy
- The method incorporates decision-maker preferences over evaluation measures and degree of belief about the likelihood of uncertain events

The case study drafted in this thesis exemplifies the analysis of a decision with limited alternatives. Although these alternatives yield some similar results, other operational aspects differ significantly, adding complexity to the process of evaluating value and trade-offs on a larger scale. Throughout the study, it became clear that in a decision-making process involving technical analysis with limited alternatives, the lower-level objectives must be carefully tailored to be able to extract the required value for effective evaluation. Therefore, construction of a decision model with a similar context should start with identifying and studying the possible alternatives.

The theory and the model presented in this thesis relate to a decision that takes place at a single point in time. However, decisions can have a longer gap between the point the decision is taken, to the point the consequences take place.

Future study can be conducted studying the consequences of time dependencies on parameters such as uncertainty, risk attitude and preferences over evaluation measures.

This Thesis has shown that Multi-Objective Decision Analysis - MODA framework can help professionals to make good decisions and achieve expected outcomes by choosing the alternative that best fits the set of goals.

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