2
Literature review

In this chapter, we conduct a literature review about the use of smart wells on reservoir development with a study about the optimization strategies of the flow control strategy as well. Here we explain what a smart system is, highlighting the benefits and challenges involved, including equipment reliability. We also describe the flexibility of smart wells and the possible strategies to manage this technology. The literature review includes the description of how reservoirs are developed and managed under considerable uncertainties concerning true reservoir properties. We finish this chapter listing some related works found in the literature that differ from each other by the way that the flow control strategy is defined, considering uncertainty and the information available.

2.1.
Smart wells in reservoir development

In recent years, some novel technologies and concepts have been developed and deployed to maintain the profitability of development of oil fields; among them, Smart Well Technology (also called Intelligent Well Technology) are among the most significant breakthroughs (Gao *et al.*, 2007). Since the first smart completion was installed in August 1997 at Saga's Snorre tension Leg Platform in the North Sea (Gao *et al.*, 2007), the smart wells have added a new dimension to commercial analysis in the oil sector (Mathieson *et al.*, 2003) and the technology application has increased exponentially (Alsyed & Yateem, 2012). However, according to Glandt (2005), implementation of any new technology in the E&P industry requires a solid business case that clearly demonstrates the incremental value.

2.2. The smart well system

The smart well system is described by Aggrey *et al.* (2006) as a permanent downhole completion that consists of sensors to measure pressure, temperature, flow rates, phase cuts, packers for zonal isolation and valves for flow control. A mandrel on the production tubing holds the gauge in place. The data transmission cable and hydraulic lines are enclosed in a protective metal tube and clamped on the outside of the tubing. The electrical or optical cable is connected to the gauges; while further electrical or hydraulic line(s) supply the required power to operate the valves. Both power and measurement systems are connected to the surface control system through the packer and wellhead penetrations. The surface system may be either data logger (monitor) or a complex optimization and control system. Successful acquisition, transmission and receipt of the data will depend on proper functioning of each and every part of the total system.

Therefore, we can summarize a smart wells system as a combination of (Armstrong & Jackson, 2001):

- Downhole sensors to sample environmental parameters;
- Downhole actuators to change the operating conditions of well; and
- Interpretation and processing algorithms to optimize reservoir/well performance.

The controlling capability is achieved by using hydraulic, electric or electro-hydraulic controlled devices (Ajayi & Konopczynski, 2003) (Sakowski *et al.,* 2005), and they are used to regulate the flow into the wellbore. The valves can be either binary on/off system (open and close only) or have variable chocking capability (Akram *et al.,* 2001). The open or closed control in which the controls only operate on the extremes, is called 'bang-bang' control (Brouwer & Jansen, 2002). These control devices can also be called, on literature, as:

- Inflow Control Valves (ICV's) (Brouwer & Jansen, 2002) (Glandt, 2003) (van der Steen, 2006) (Kavle *et al.*, 2006) (Leemhuis *et al.*, 2007);
- Flow Control Valves (FCV's) (Van der Steen, 2006);

- Interval Control Valves (ICV's) (Armstrong & Jackson, 2001) (Akram *et al.*, 2001) (Han, 2003) (Ajayi & Konopczynski, 2003) (Ajayi & Konopczynski, 2005) (Aggrey *et al.*, 2006).

As described, the flow control valves allow the creation of a 'choke' restriction to the flow with a smaller (often much smaller) cross-sectional area than that of the tubing. There is a wide variety of flow control valves available, with many common features and some differences, sharing some properties as: tubing retrievable (wireline retrievable available for gas lift applications); can be used for either production or injection; can be installed as either annular control valves or inline control valves; sand control; suitable for environments with scale deposition. The choice of equipment may depends of the reliability, complexity, number of valves required

These valves are located within the main completion bore at each desired zone and isolated by packers. Each interval control valve regulates the flow by creating a pressure drop between the annulus and the production tubing via a variable orifice, which allows the operator to select or commingle production from each zone at a specified rate (Armstrong & Jackson, 2001). Besides the flow control devices, Konopczynski *et al.* (2003) list others elements of smart wells, as:

- Feedthrough isolation packers – to realize individual zone control and ensure segregation of separate hydrocarbon pools, each zone must be isolated from each other by packers incorporating feedthrough facility for control, communication, and power cables;
- Control, communication and power cables – smart well technology requires one or more conduits to transmit power and data to downhole monitoring and control devices. These may be hydraulic control lines, electric power and data conductors, or fiber optic lines. For additional protection and ease of deployment, multiple lines are usually encapsulated. When hydraulic technology is used, at least one control line is normally needed per valve and the number of hydraulic lines can be limited;
- Downhole sensors – a variety of downhole sensors are available to monitor well-flow performance parameters from each zone of interest. The sensors generally provides measurements about temperature and

pressure of each zone. Is not common, but also can be possible to have measurements about the flow on each zone;

- Surface data acquisition and control – with multiple downhole sensors providing “real-time” production data, the volume of data acquired can be overwhelming. Systems are required to acquire, validate, filter, and store the data. Processing tools are required to examine and analyze the data to gain insight into the performance of the well and the reservoir. In combination with the knowledge gained from the analysis, predictive models can assist in the generation of process-control decisions to optimize production from a well and asset.

2.2.1. The benefits

The Smart Wells Technology enables operators to have ‘real-time’ data from the wellbore (Armstrong & Jackson, 2001), so it has the ability to acquire the relevant information required for future decision-making. Consequently, the operators can remotely monitor and control the production of hydrocarbons through remotely operated completion systems (Gao *et al.*, 2007), i.e., it enables the wellbore architecture to be reconfigured remotely by the operator in response to this data without shutting in the well and introducing a workover rig (Armstrong & Jackson, 2001). Real-time data acquisition is possible with either conventional electronic or emerging fiber optic instrumentation (Sakowski *et al.*, 2005).

This technology has been applied in many assets to increase production and reduce intervention costs, especially in offshore fields. It enables quick reaction to unexpected events during the life of a reservoir, such as delaying early water breakthrough. This technology becomes particularly important in the case of offshore fields where well costs, injection costs, liquid lifting costs (oil + water) and water processing costs are considerably greater than in onshore wells. The introduction of intelligent well systems is rapidly moving from the more obvious, high-cost offshore applications to more revenue-sensitive operating arenas, including mature and marginal fields (Gao *et al.*, 2007).

The potential benefits of employing smart well technology are numerous, and these benefits have been demonstrated in practical applications. These benefits include:

- Automated regulation of flow by down-hole inflow control devices (Almeida *et al.*, 2010);
- Pressure and temperature data acquisition from each zone (Chukwueke & Constantine, 2004) (Armstrong & Jackson, 2001);
- Real-time measurement and transmission of reservoir measurements for better reservoir management (Chukwueke & Constantine, 2004);
- Water and gas coning control (Leemhuis *et al.*, 2007) (Yeten *et al.*, 2002), extending the life of wells and reserves (Almeida *et al.*, 2010) (Ajayi *et al.*, 2008);
- Reduce need of intervention procedures (Chukwueke & Constantine, 2004)(Robinson, 2003) (Armstrong & Jackson, 2001) (Ajayi & Konopczynski, 2003) (Sakowski *et al.*, 2005) (Almeida *et al.*, 2010);
- Control multiple zones independently (Ajayi & Konopczynski, 2003) (Yeten *et al.* , 2004), accelerating production between zones to maintain a plateau for expected period of time (Ajayi & Konopczynski, 2003) (Sakowski *et al.*, 2005);
- Commingling production from separate reservoir to increase total recovery through time (Han, 2003) (Konopczynski *et al.*, 2003);
- Reduce well count required to drain reserves (Sakowski *et al.*, 2005) (Ajayi & Konopczynski, 2003), also saving on surface facilities costs (Sakowski *et al.*, 2005);
- Enhance ultimate recoverable reserves through improved reservoir management (Sakowski *et al.*, 2005).

These benefits are amplified many times over in deepwater and subsea operations due to the high costs and technically demanding challenges associated with these locations. Yeten *et al.* (2004) affirm the benefits of these smart wells can be determined by optimizing their operation to maximize the net present value (NPV) or recovery. According to Robinson (2003) the applications and benefits of remote completion monitoring and control depend on the type of well considered in each development, in particular, multizone or multilateral wells (both injector and producer) may benefit greatly from remote control.

2.2.2. The challenges

Based on a literature review of past experiences, common challenges in applying smart-well concepts and hardware include: accounting for geological, reservoir and resource-price uncertainties in deciding how to operate the down-hole inflow control valves (Almeida *et al.*, 2010) (Yadav & Surya, 2012), balancing the benefits of smart wells against their cost in mature fields (Akram *et al.,* 2001), accounting for the reliability of down-hole inflow control valves and sensors (Cullick & Sukkestad, 2010), and identifying suitable candidates for smart wells (Ajayi *et al.,* 2007). These challenges share a common theme: the need to optimally design, value, and control the intelligent well hardware, under uncertainties, and thereby to determine if smart wells are an advantageous technology for the field in question.

Chukwueke & Constantine (2004) discussed these challenges and also the benefits delivered and the lessons learned during the successful application of smart well technology. Kavle *et al.* (2006) describe the potential risks posed specifically to intelligent completions by scale deposition and also demonstrate the possible benefits that can be added to scale management as results of using smart well technology. Dhubaiki *et al.* (2013) described many benefits that have been harvested through utilizing smart well completions in one of the Saudi Aramco fields, affirming that the benefits justify the cost of installation.

Smart technology is fast gaining acceptance in the completion of heavy oil fields (Cullick & Sukkestad, 2010), and is highly beneficial in enhanced oil recovery (EOR) operations (Gao *et al.,* 2007). The goal of smart wells is the automation of as much of the production process as is achievable, so as to improve the net present value (NPV) of an asset, which is achieved by maximizing production and minimizing costs. This smartness can be extrapolated to the field as a whole, and van der Steen (2006) discussed the “evolution” from smart well installations to the delivery of a fully integrated smart field.

In summary, smart completions select optimal operational combinations, and ensure excellence in the different stages of design, planning, installation and implementation. Though this does not guarantee a successful operation, it increases the chance to become a valid investment.

2.2.2.1. Reliability

One of the barriers to smart well deployment is the inability to properly quantify the asked value due to the possible loss of the smart system’s ability to function properly to achieve the required reservoir or well management objectives (Aggrey & Davies, 2007). Completion failures reduce the field total profitability through decreased revenue (decreased system availability) and/or increased OPEX (more workover cost), consequently when moving into deeper water, the economic penalty for delayed/lost production becomes greater (Brownlee *et al.,* 2001). Furthermore, subsea well system repairs and interventions also become more expensive and are associated with longer delays due to availability and mobilization times for the required repair vessels (Brownlee *et al.*, 2001).

Over the years, the industry has made extensive studies of the design improvements required for reliable smart well systems and many advances have been made to improve systems reliability. According to Naldrett & Ross (2006), during the relatively early period of permanent monitoring installations in the mid-1990s only 80% of permanent gauge systems were still operational after 2 years, and in the case of gauge failure we lose the ability of measurements acquisition (Veneruso *et al.*, 2000). From 1995 to 2000 reliability improved significantly, with 90% of installations still operating after 2 years. Aggrey & Davies (2007) affirmed that published reliability factors range from 70 to 98% for five year survivability, for smart well equipment, but the exact value depends on the technology chosen for communication (hydraulics or electrical) and on the level of complexity such as the number of zones and the type of control (on/off, multi-position or infinitely variable) specified for the valves.

According to Ajayi *et al.* (2008), the smart completion is becoming a major component of many offshore field development activities and this attraction could be due to the significant improvement in the robustness and reliability of the systems, wider understanding of the workings of the components and demonstrated economic values of the technology. The reliability improvement could be associated with an increased number of worldwide installations and the fact that the lessons learnt from these installations have resulted in better integration on design of the system components.

Ajayi *et al.* (2005b) affirmed that an important part of any reliability program is to define what constitutes a failure, since the smart completion is generally part of a much larger well or field structure and may depend on several external factors in order to deliver the overall “mission reliability” expected by the customer. In view of this, the authors defined separately mission and system reliability as:

- Mission reliability, the customer expectation that reservoir zone function will survive as specified within the target implementation environment. Mission failures include smart completion system failures, third party equipment failures (such as gravel pack systems, subsea wet connectors) or reservoir zone failures (such as scale build up);
- System reliability, the probability that the smart completion equipment will survive as specified within the target implementation environment. System failures are anything associated with the equipment design (such as connectors, electronics, cables etc.).

The difference between mission and system reliability provides insight into the importance of external factors such as interfaces, integration management and specific infrastructure (Ajayi *et al.*, 2005b). About equipment survivability, Veneruso *et al.* (2000) affirms that for permanent downhole installations the corresponding ages have been characterized as:

- Early failures dominated by installation, cable and mateable connector related problems;

- Medium term failures mainly related to connections at the tree, tubing hanger, annular safety valve or packer; also some short circuits at the gauge start to appear;
- Later failures reported as a short circuit at the gauge or at a connection.

The type of equipment failure that interests us are failures which cause us to cease to have control over the valve, either due to failure of the valve itself or due to failure of the communication with the valve. If we do not take into account the possibility of such failure when performing a flexible optimization, the resulting policy will have two key shortcomings: 1) it will assign too high a value to the smart completion, and 2) it will not take advantage of the ability of a smart completion to adapt and mitigate when failure occurs. Flexible optimization seeks strategies that are robust in the eventuality of failure by adjusting other valves so that they reduce the consequences of failure.

When valves fail, they usually became stuck at a particular setting that depends both on the type of valve and on the mode of failure. For example, if the failure is caused by damaged communication line, then the valve may remain stuck on its previous setting. For some hydraulic valve types, a decrease in valve aperture is achieved by cycling the valve settings through increasing apertures until the setting ratchets down again through decreasing apertures. In this case, during the valve adjustment there is a theoretical risk that the valve may fail in a setting somewhere between its previous setting and the newly requested setting, as for example, fully open or fully closed.

Not just valves, but sensors also can fail and Aggrey *et al.* (2006) affirm that an error (e.g. instrument drift) in the pressure reading may result in an inaccurate rate or phase cut inference. An error in the measurements representing “poor data” that negatively reflects on ability to adjust the valve setting to the correct value.

According to Han (2003), a major barrier to the adoption of smart well technology has been the lack of a method to quantitatively define the value associated with various applications of the technology. In 2006, Naldrett & Ross (2006) emphasize that the industry has clearly embraced the role of smart well completions in improving reservoir management, optimizing production and recovery, and minimizing well intervention. For them, the barrier to adoption is reduced, as operators, small and large, are now more confident in the technological advances made to improve systems reliability and economies.

So, how to realize the smart wells value, balancing their benefits against their challenges? Ham (2003) emphasizes that to realize the smart well value proposition, it is important to understand how the reservoir can be developed by applying the functionality provided by the smart well system, and reservoir numerical simulation can be utilized to model the reservoir and demonstrate the incremental production performance enabled by the different levels of "smartness" provided.

In order to arrive at an informed decision on the deployment of smart wells, one must first quantify their benefits. The benefits of these wells can be determined through optimization of the net present value (NPV) (Oxford, 2008) or recovery (Yeten *et al.,* 2004). For this reason, the optimization process of flow control strategy from smart completions has attracted interest in the area of reservoir development and management.

2.3. Flow control strategy

The value of the smart well technologies, according to Robinson (2003), is derived from the ability to actively modify the well configuration and performance through flow control and to monitor the response and performance through downhole data acquisition. Then, Robinson (2003) affirms that the analysis of these data combined with predictive reservoir simulations enable realization of greater asset value by the utilization of this virtual feedback control system.

Flow control refers to the ability, at a minimum, to open or shut off a zone or reservoir in a commingled well at will, an unlimited number of times, without intervention (Konopczynski *et al.,* 2003). Therefore, the ability to shut-off zones, offered by smart wells, is important to prevent crossflow between reservoirs and to exclude production of unwanted effluent (water and/or gas).

We must keep in mind that data interpretation and analysis are important steps in smart technologies since it is through these processes that we make decisions on dynamic control actions during well operation. The data types available from smart well technology include the differential pressure i.e. the pressure before/inside/after the flow control valve, and temperature (Zhu & Furui, 2006).

According to Yeten *et al.* (2002), one approach for using smart well technology is to wait for problems to occur (known by the measurements) (e.g., water coning) and then reset the instrumentation to mitigate them. But Yeten *et al.* (2002) also describe other approach that uses downhole inflow control devices in conjunction with a predictive reservoir model, allowing for the optimization of reservoir performance rather than just the correction of problems that have already occurred. So, the flow control from smart completion can be done based on these two different strategies, called “reactive” and “proactive” (Yeten, 2003).

With a reactive control strategy, the valve is operated in reaction to current and/or historical information (measurements). For example, if there is an increase in water production in a given region, we might react by restricting the flows in this region, favoring the production in another region that has a lower water production.

With a proactive strategy, the valve operation is done with respect to a forecast that is informed by currently available information, i.e., it acts to remediate foreseen issues before they become critical problems. For example, from the beginning of production there is a search for a valve setting satisfying certain objectives such as delay of water breakthrough to anticipate the production or to achieve a higher recovery of oil in field.

The proactive strategy implies an optimization process with a long forecast horizon and the need for a reservoir model that fits this forecast horizon. In summary, the proactive strategy seeks to prevent an undesired future result, while the reactive strategy actuates the valves when the undesired event occurs. In the context of smart fields, the continuous monitoring of pressures and flow rates of the wells can lead to continuous updates about the flow model over time. Thus, especially in a design phase where there is a large number of uncertainties in the flow model, the results obtained in an optimization process using proactive control has a more qualitative value, indicating if the field has potential gains from smart completions.

2.4. Optimization of flow control strategy

The optimization of the flow control strategy for a reservoir with known properties is in itself a challenging operations research problem, which aims to find the optimal settings for the control valves of the smart wells. This optimization becomes more complex when the reservoir properties are uncertain, because for each potential valve setting, a forecast obtained through a potentially expensive reservoir simulator, for each of the possible reservoir scenarios is required. Although this significantly increases the optimization time, the results are more robust to reservoir uncertainty because they consider the potential outcomes over many reservoir scenarios. Despite the uncertainties about the reservoir geological characteristics, some optimization strategies consider uncertainty fully resolved before any decision needs to be made about the flow control strategy.

2.4.1. Optimization without uncertainty

The idea of an optimization strategy considering no uncertainty is to assume that all reservoir properties are truth. With this assumption, the optimization strategy seeks for the optimum valve settings that maximize the net present value (NPV), deterministically. This optimization strategy can indicate if a field does not have potential for significant gains in a stated objective function from the deployment of such a smart completion, considering the perfect information about the reservoir properties. We briefly describe some works that investigate the value of smart wells considering no uncertainty about the geological scenario.

Armstrong & Jackson (2001) investigated the application of smart well technology to optimize recovery from multiple pay zones by managing water breakthrough. Their paper is focused upon the use of smart well technology to monitor and optimize production from wells containing a single tubing string completed in multiple pay zones. They concluded that a low well population and a poor reservoir connectivity well increase the benefits of this technology.

Brouwer & Jansen (2002) proposed a methodology that use optimal control theory to develop an optimization algorithm for the valve settings in smart wells.

They developed a systematic algorithm to optimize the valves maximizing the net present value and investigate the effect of well constraints on the scope for optimization.

Ajayi & Konopczynski (2003) proposed an optimization based on the gradient-based method and iterative process, using command language, to compute optimal valve settings to meet the desired objective function. The goal was to control the zones at time intervals in order to achieve assigned maximum production for as long as possible.

Ajayi & Konopczynski (2005) described a study to identify the best application of smart well technology in the field and quantify the gains from such applications. They used gradient-based method to assign the optimum valve settings. Even so, the authors affirmed that in practice, the development engineer would be required to evaluate the uncertainty around the predicted water breakthrough time before deciding on the need of smart completions for this well.

Leemhuis *et al.* (2007) proposed an approach to gas coning control by the optimization of flow control strategy. They implemented a proportional integral derivative feedback controller, which controls the gas fraction in a well by changing its inflow control valve settings or the wellhead choke of a smart well. Their purposes were to keep gas fraction in a well below a certain level, to prevent damage to topside equipment, and to optimize production by taking the effects of natural gas lift and choking of the production flow into account.

Emerick & Portella (2007) presented an implementation of method to optimize the production in intelligent wells varying the wells inflow control valves settings using an optimization procedure that uses direct search methods. In the optimization process they divide the simulation period into steps, performing an optimization to define the valves settings for each step, as was proposed by Yeten *et al.* (2002).

Barreto *et al.* (2012) proposed a methodology to improve production strategy using water cut as an economic indicator and as a variable of the optimization process. They used the water cut parameter to make evaluations and help decide whether the strategy could be improved or not and to choose what could be changed before the perforation of wells. An Evolutionary Algorithm was used to optimize the value of the water cut and a manual optimization was used to improve the production strategy, changing well completion perforation in grid block and well location.

In this section we have described a range of control techniques that have been proposed to optimize production from smart wells, and these has showed that flow control strategies may add significant value in many reservoirs. Yet reservoir models are always uncertain to some degree, and all the previous works ignored this uncertainty. Ham (2003) affirms that much of the value associated with a smart well application is generated through its ability to provide flexibility to better manage future events, both expected and unexpected. The uncertainty around the potential of future revenue generating events and when those events will occur is generally acknowledged by the industry. Therefore, corroborating with Ham (2003) we can say that deterministic analyses can be inadequate to handle evaluations where the timing of future events or their exact effects on cash flow is not itself deterministic in nature.

2.4.2. Optimization with uncertainty

There are three principal attributes/techniques by which the challenge of operating under uncertainty may be reduced or minimized to a manageable degree: robustness of solutions; acquisition of information; and flexibility of solutions. All three of these should play an important role in reservoir management (Moczydlower *et al.*, 2012), but at times it is difficult to decide what method, or combination of methods, will best minimize the primary/influential uncertainties. For many flexible solutions, extra consideration often needs to be given to cost: both direct, due to more expensive equipment and procedures, and indirect caused by a possible equipment failure.

In order to make an informed decision as to whether the benefits afforded by a particular reservoir management solution justify their additional cost, we need to determine both an optimal strategy for the management of these technologies and a method to determine the additional value that they provide, *e.g.*, increased/accelerated oil production and/or reduced water management costs.

In the follow sections we describe these general strategies (robustness, information, flexibility), explaining how they may provide a meaningful and substantive valuation in the presence of uncertainty.

2.4.2.1.
Robustness

A robust solution is one that is appropriate for most, if not all, possible reservoir conditions. Inevitably, the robust solution represents a compromise, reducing the NPV under more favorable reservoir conditions so that an increase in NPV is possible under less favorable circumstances. According to Moczydlower *et al.* (2012), the robustness approach is often chosen when the project cannot wait for the information or when its acquisition will not reduce the uncertainty/risk to an acceptable level.

Robust strategies can be depicted by a decision tree, i.e., a graph that uses a branching method to illustrate every possible outcome of a decision, describing graphically the decision to be made, the events that may occur, and the outcomes associated with combinations of decisions and events. Figure 2.1 illustrate this fact, where an arc (that denotes a multiplicity of decisions) represents the decisions, while the decision node is represented by a square and the uncertainty node is represented by a circle. Likewise, the arc following the uncertainty node denotes a multiplicity of possible outcomes. The robust strategy is the one that maximizes the expected NPV across the decision space with respect to the uncertainties.

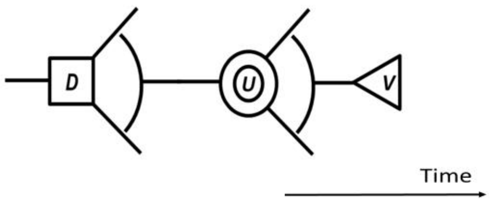

Figure 2.1: Compact representation of a decision tree, from which a robust strategy may be determined.

If U represents the space of uncertainties and *D* represents the space of all possible decisions then the robust valuation (V_{robust}) and development strategy (d_{robust}) is given by

$$V_{\text{robust}} = \max_{d \in D} \underset{u \in U}{\mathrm{E}}(V|d,u), \tag{2.1}$$

$$d_{\text{robust}} = \arg\max_{d \in D} \underset{u \in U}{\mathrm{E}}(V|d,u). \tag{2.2}$$

We can easily derive the expression from the decision tree in Figure 2.1 by backwards calculation, i.e. following the decision tree from right to left; starting at the final "known" NPVs and ending at the initial "uncertain" expected NPV. When passing through the uncertainty node we calculate the expected value that each decision yields, and when passing through the decision node we determine the decision that yields the highest expected NPV. Like this, we can reach the root of the decision tree, where we will have recovered the optimal expected value and have a description of the optimal strategy.

With increased flexibility, the number of possible development strategies increases, and so a new robust strategy with a higher valuation might be found.

2.4.2.2. Information

The acquisition of appropriate information should allow one to reduce uncertainty and limit the number of possible candidate reservoir priors/conditions. According to Moczydlower *et al.* (2012), a limitation of this is that normally it only measures the uncertainties that "we know we do not know", i.e., we just account for known uncertainties, and sometimes the uncertainties that "we do not know that we do not know" may be critical. In these cases, the acquired information may reveal some of these unknown uncertainties, increasing its predicted value substantially, i.e., the true value of information is always even higher than what we predict.

Information, if properly used, is useful at all stages: from exploration; through initial development; and into production, but Moczydlower *et al.* (2012) highlighted that the information is only valuable if it is available before the key decisions of the project are made.

The inclusion of measurement information can resolve some uncertainty before decisions are made. The value of perfect information, or the value of clairvoyance (Barros *et al.*, 2014), is the additional value that could be realized if all uncertainty was resolved prior to making the decision, as shown in Figure 2.2. The valuation with perfect information is given by

$$V_{\text{clairvoyance}} = \underset{u \in U}{\mathrm{E}} \max_{d \in D} (V|d, u). \tag{2.3}$$

In that case, all uncertainty is resolved prior to making the decision and for that reason this give a higher value. In the real world, even with measurement data, we are unable to fully resolve all uncertainty at the time of making a decision. As shown in Figure 2.3, some of the uncertainty is resolved before the decision is made and so the valuation is given by

$$V_{\text{information}} = \underset{m \in M}{\mathrm{E}} \max_{d \in D} \underset{u \in U|m}{\mathrm{E}} (V|d, u). \tag{2.4}$$

This approach is useful for the valuation of future measurements, *i.e.*, which future measurements will best guide the future adjustments to the FCVs so that the expected NPV is maximized. For example, to value and manage FCVs we might incorporate pressure and rate measurements, both downhole and surface, noting that these future measurements will be affected by future valve control decisions.

This information can be extremely valuable and instructive for future operational management and decision making of the reservoir. However, our ability to fully utilize this information depends on the degree of practical, operational, flexibility we have to alter our production (development) strategy. The value of the information during production is, therefore, inextricably linked to the degree of operational flexibility of the reservoir. This leads us smoothly to the next topic: flexibility.

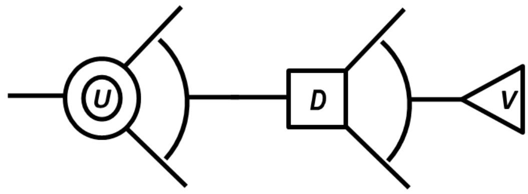

Figure 2.2: Decision tree representing the value of 'clairvoyance', i.e. information that allows us to completely resolve uncertainty. Note that the uncertainty is resolved before any decision is made.

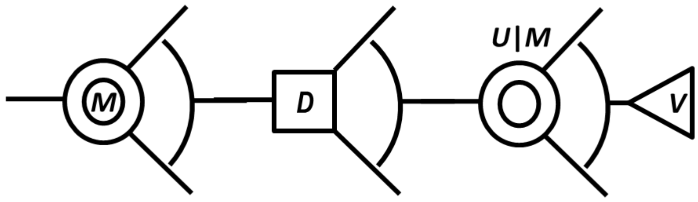

Figure 2.3: Decision tree representing a more realistic value of information in reservoir engineering, in which only part of the uncertainty is resolved by the measurement M at the time that a decision must be made.

2.4.2.3. Flexibility

A flexible strategy for the development of a reservoir provides the opportunity to react to the results of future measurements, *e.g.*, the production history may show that a region of the reservoir is compartmentalized or not. If our development strategy is sufficiently flexible, we will then be able to decide whether an additional injector is required or not. The value of flexibility may be calculated considering different possible scenarios, the probabilities associated with them and the impact in each of them of the availability or not of the referred flexibility (Moczydlower *et al.*, 2012).

Many technologies exist that can enable us to easily alter our development strategy in the future, including interval control valves that allow completed well-segments to be either choked or isolated, providing flexibility in the future production from individual reservoir zones/regions. Interval control valves can also be installed in injectors for greater control over pressure maintenance.

We may seek such flexibility either because we know, today, that an alternative strategy will be required in the future, or because we expect that we will become better informed about the geology of the reservoir, and want more options to aid in future reservoir development. In this thesis, we will focus on the valuation of smart wells, *i.e.*, flow control devices accompanied by permanent downhole reservoir and production monitoring equipment.

As we have already noted, in the real-word many different types of uncertainty can be present, such as geological, technical and economic uncertainties. The incorporation of uncertainty and the use of information on flow control strategy definition can therefore be crucial. Despite this, most works in the literature of smart-well optimization either do not account for uncertainty or do not account for the possibility of acquiring future information. These optimization strategies therefore yield values for the smart completion that are respectively too high or too low.

The next section includes a literature review describing some related works, with an overview about flow control strategies that consider uncertainty, emphasizing the different ways to use the available information to reduce the uncertainties over the time.

2.5.
Related works

Addiego-Guevara & Jackson (2008) affirmed that it is risky to develop a control strategy based on the predictions of a model that is unlikely to capture the true reservoir behavior. Furthermore, since the information acquisition can reduce the geological uncertainties, considering information during the strategy definition allows one to make more certain decisions at the time of choosing the valve settings to be used. Against to reservoir uncertainties, many studies recognize the problem of incorporating it in the optimization workflow. Nevertheless, the optimization strategies can still be made considering the geological uncertainty but ignoring the information in some level, as we follow describe.

The following section is a literature review, collecting works that in some way propose to find the flow control strategy to smart wells, valuing this flexibility under geological uncertainty. Most studies in the literature either do not account for the possibility of acquiring future information, or they treat uncertainty by optimizing a few representative models individually (e.g., assuming that they represent optimistic, realistic or pessimistic scenarios). They then obtain separate "optimal" strategies for each selected realization. These optimization strategies therefore yield values for the smart completion that are respectively too low or too high. We are calling these optimization strategies as optimization with only prior information, and optimization assuming clairvoyance.

2.5.1. Optimization assuming clairvoyance

In valuation of flexibility, the optimization of the flow control strategy may uses one or more ensembles of geological realizations (reservoir models) to account for uncertainty. In some cases, we can assume that the perfect information becomes available through a revelation of the truth at a certain moment in time. Such clairvoyance in an optimization implies that it requires only a single (true) model, and consequently, it is computationally significantly less demanding. We describe this approach as optimization assuming clairvoyance. The optimization assuming clairvoyance seeks the optimum flow control strategy for the geological model that represent the real reservoir, i.e., it considers perfect information about the reservoir.

The term clairvoyance is used in the literature to refer to a situation whose all possible answers are considered due to an uncertainty situation (Beyth-Marom *et al.*, 1985). The valuation with clairvoyance is given by eq. (2.3), detailed in chapter 2. The uncertainty scenarios are commonly called, for example, P10, P50 and P90. This approach can be used to investigate more than one possible geological model, by considering a determinist optimization for each geological model available, allowing the evaluation of the value of flexibility for multiple uncertainty scenarios. Optimizing representative uncertainty models individually does not yield a single operational strategy, but instead an individual operational strategy for each representative model. The ideal strategy is therefore conditioned on the unknowable (knowledge of which model is the true model). This approach is useful for indicating if the field has the potential for significant gains in a stated objective function from the deployment of such smart completion. In the remainder of this section, we briefly describe some works that optimize the flow control settings with clairvoyance, considering a single reservoir model (as a representative model) in the optimization.

Yeten *et al.* (2002) described a gradient-based optimization procedure for the control of a smart multilateral well. Their methodology uses an optimization strategy that divides the entire simulation period into n steps and optimize the valve settings for the first period, seeking the optimum settings for the entire simulation period. Once this optimization is completed, they proceed to the next optimization time step by restarting the simulation from the end of the previous optimized step. This is done for each optimization time step, with the objective of maximizing the cumulative oil production. Although the optimization is done in steps over all time, this methodology does not take into account the information gained in the future.

Yeten *et al.* (2004) proposed the use of gradient-based optimization technique in conjunction with a reservoir simulator. The optimization accounts for uncertain geology considering five simulation models, each having a different realization of the geological description.

Aggrey & Davies (2007) applied a gradient based, automatic, optimization software to optimize the performance of a smart well, using as an objective function the maximization of oil recovery. Even though the authors described a methodology that can be used to calculate the expected value involving a Monte Carlo setup to capture the impact of uncertainties, including geological realizations, they performed the geological uncertainty with just five discrete model realizations of differing permeability.

Meum *et al.* (2008) presented an algorithm for optimizing reservoir production using smart well technology. To compute the optimum control settings for a known benchmark case, they implemented a nonlinear predictive control model, interfaced to a reservoir simulator, used as a simulation and prediction model.

Bovolenta *et al.* (2012) improved a methodology that quantify the information on oil field development, incorporating operational flexibility to the project by reducing the number of dry wells and through a more accurate dimensioning of the production strategies and facilities.

Ghosh & King (2013) proposed to optimize the flow control valves operation considering a proactive strategy, using the Simulated Annealing algorithm in conjunction with a commercial reservoir simulation to maximize the NPV. Three geological scenarios are used to incorporate geological uncertainty in the optimization process, and each one was analyzed individually.

Barreto & Schiozer (2014) proposed an optimization process that uses economic and technical indicators to speed up the process. The main goal of the method is to reduce the number of variables and the search space of the problem by prioritizing well regions where a valve operation has more technical and economic potential. Their methodology combines a low-cost framework to select more potential regions to evaluate smart well implementation and a free-derivative variation of the steepest ascent method to find the best solution for the control design for that specific region, considering on/off valves.

The optimization assuming clairvoyance have a more qualitative value, indicating if the field (or at least the representative scenario considered) has potential of significant profits using the smart completion. In reality, we must also plan and operate under uncertainty. For this reason, the results obtained by this optimization strategy cannot be used to give either a quantitative valuation (except as an upper bound) of the benefits of flow control valves or a realizable strategy for the control of the valves considering the geological uncertainty. Salomão *et al.* (2015) affirm that to choose as a reference the most likely scenario, and then, based on this scenario define the oil recovery strategy cannot be the best decision. We agree with them that the most suitable and reliable is to consider, at the same time, multiple scenarios to build a recovery strategy that will be profitable in different situations.

2.5.2. Optimization with prior information

Another way to value flexibility is to consider all prior information available about the reservoir, instead of considering perfect information to optimize the flow control strategy. While optimization assuming clairvoyance evaluates a single reservoir model, optimization with prior information considers all geological uncertainty models available, and the objective is now an expectation over all scenarios.

In other words, optimization with prior information considers optimization under uncertainty – without future information – seeking to determine the strategy that maximizes the expected NPV, yielding a strategy that, on average, represents the best solution over the ensemble of scenarios. The valuation without future information is given by eq. (2.1) and eq. (2.2), detailed in chapter 2. Bellow, we briefly describe some works that optimize the flow control valves considering the prior information.

Schiozer and Silva (2009) compared smart and conventional wells developing and applying both types of wells considering the availability of different platforms, each one with a particular fluid treatment capacity. In their work, the optimization strategy is based on reactive control, and the average NPV was used to evaluate the strategies under uncertainty.

Almeida *et al.* (2010) proposed a decision support system, based on Evolutionary Algorithms, able to optimize smart well control, where the objective of the optimization model was to find the valve setting, which maximize the expected net present value, considering three representative geological scenarios.

Marques *et al.* (2013) proposed a methodology to estimate the value of flexibility through a risk-return analysis in which a company profile is taken into account by the iso-utility curve. Their methodology was an extension from the value of information assessment under uncertainty. They used Latin Hypercube technique to generate the uncertainty geological scenarios, seeking for the strategy that is optimal in average terms.

Although the optimization with prior information considers an expectation over uncertainty scenarios, this does not include the possibility of acquiring new information in the future, i.e., this approach does not account for the diminishing of reservoir uncertainty over time as new information is gathered. In fact, as time passes, new information about the reservoir is acquired, and the consequent reduction in reservoir uncertainty enables better decision making. Thus, optimization policies that ignore future information forgot the potentially significant value imparted by that information, i.e., they do not account for the reduction of reservoir uncertainty over time that is forthcoming from new (and relevant) information that is gathered, and therefore result in a sub-optimal strategy. Such a methodology yields the optimal purely-proactive strategy under uncertainty.

2.5.3. Optimization with future information

As we have been showing, usually we must define the flow control strategy under uncertainty, furthermore in a real situation, with the acquisition of information, it is possible to reduce uncertainties and make more confident decisions. Despite the possibility of acquisition of information reducing uncertainty over time, the incorporation of future information on the optimization strategies is not so common. Optimization with future information incorporates such "prescience" by using reservoir simulation to model the possible future reservoir outcomes of such measurements and the performance of the asset as a whole.

Armed with such information, Dynamic Programming can be applied to a decision tree via a backpropagation algorithm (Bertsekas, 2007) implemented in such a way (Prange *et al.*, 2009) that would yield the optimal valve settings as a function of possible future reservoir measurements. Although dynamic programming may find the optimal strategy - in theory - in practice the number of reservoir simulation runs required to sufficiently cover the very large solution space increases exponentially with the number of valves and their adjustment times. The combinatorial explosion makes the search for an exact-solution completely impractical.

Barros *et al.* (2015) proposed a methodology that combines tools such as robust optimization and history matching in an environment of uncertainty characterization, considering optimization with prior information to determine the production strategy that maximizes a given objective function over the ensemble and then estimating the value of information. The authors address the usefulness of information in terms of the reduction in uncertainty of a variable of interest, so they consider the measured data (future information) to update a prior ensemble of reservoir models, resulting in a posterior ensemble, which forms the basis to compute various measures of information valuation. Their approach considers the optimization with future information to reduce the uncertainty over the time and make better decisions, for which they assume that one realization of the uncertainty scenarios is the truth reservoir. This synthetic truth reservoir is simulated to provide the data measurement used to reduce the uncertainty over the time horizon. Since this procedure can choose one synthetic reservoir model each time as the truth reservoir, the full procedure needs to be repeated several times. This last fact shows that their proposed approach requires a very large number of reservoir simulations.

As we have noted in this bibliographic review, there are several ways to consider the uncertainty and information during the optimization process and we must take account all the concepts learned with then. In this way, we agree with Salomão *et al.* (2015) that affirm that when information is considered as perfect, it is immediately incorporated into the plan, otherwise multiple scenarios will persist for a longer period, making it necessary to apply strategies that can be effective in different conditions, and can be matched as soon as the real scenario is revealed.

We can highlight the importance of using all available information to make better decisions. Fraga *et al.* (2015) confirm in their work the importance of acquiring static and dynamic information: not only geological information but also, and foremost, dynamic data that would support the definition of robust development plans. For that reason, the development strategy can take into account production systems with flexibility to work in different uncertainty scenarios, which will be revealed during real reservoir development.

To consider future information, while reducing the number of required reservoir simulations, we propose in this thesis an approximate approach that replaces the backward recursion of dynamic programming with a forward recursion. This reduces the number of simulations to a feasible value, while still incorporating the reduction of reservoir uncertainty through the acquisition of future information. The next chapter (chapter 3) includes a theoretical foundation that can be useful to better understand the approach proposed in this thesis, which we describe in detail in chapter 4.