A Bayesian approach to cost estimation for offshore deepwater drilling projects

By

Evans Akwasi GYASI

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Declaration

I hereby declare that this dissertation is an original piece of the authors own research which fulfils the requirements of the degree of Doctor of Philosophy (PhD). This do not contain materials which have been accepted for the award of any other degree or diploma in any college, university or institute of higher learning. I have incorporated my original work submitted in February 2016 in this resubmission. I further declare that to the best of my knowledge and belief this work has never been previously published or written either partly or jointly in any form, except for those sections that have been cited and appropriately acknowledged in the dissertation. This thesis is submitted to the University of Warwick in support of my application for the degree of Doctor of Philosophy.

Publications and conference presentations

<u>Publications (conference proceedings-peer reviewed)</u>

1. Gyasi, E., A. and Marshall, J. (2015) Minimizing Offshore Drilling cost overrun through Efficient Cost Modeling. ENTECH 2013 - ENERGY TECHNOLOGIES CONFERENCE. Istanbul, Turkey December 21-22, 2015

2. Gyasi, E., A. and Marshall, J. (2014) Effective cost control a key strategy for efficient exploitation of Nigeria marginal oil fields: case study of Ogbelle, Umusadege, Ibigwe and Ebendo". ICCE 2014: 3rd International Conference & Exhibition on Clean Energy October 20-22, 2014. Quebec, Canada.

3. Warwick University: WMG 2014 Innovation Conference, International Manufacturing Centre July 10-11, 2014.

4. Gyasi, E. A. and Marshall J. (2013) Improving Cost Engineering in the Upstream Oil and Gas sector. ENTECH 2013 - ENERGY TECHNOLOGIES CONFERENCE. Istanbul, Turkey December 26-28, 2013.

5. Gyasi, E., A. And Marshall, J. (2013) The future of oil and gas supply amidst persistent cost overrun: A review. ICCE 2013: 2nd International Conference

and Exhibition on Clean Energy (ICCE) 2013, September 9-12, Ottawa-Canada.

Oral Presentations (peer reviewed)

1. System Engineering Group-Warwick Manufacturing Group PhD progress presentation on “Cost Estimation model for offshore Deepwater drilling project” September 2015.
2. ICCE 2014: 3rd International Conference & Exhibition on Clean Energy October 20-22, 2014. Quebec, Canada.
3. Warwick University: WMG 2014 Innovation Conference, International Manufacturing Centre July 10-11, 2014.
4. ICCE 2013: 2nd International Conference and Exhibition on Clean Energy (ICCE) 2013, September 9-12, Ottawa-Canada
5. Warwick University: WMG 2013 Annual Review presentation, September 2013
6. Warwick University: WMG 2013 Conference, Poster presentation, March 2013
7. Warwick University: 2013 Poster Competition Presentation July 2013
8. Warwick University: WMG 2012 Annual Review presentation, August 2012
9. Warwick University: Envisioning and Innovation Program Presentation, BBC Coventry and Warwickshire July 2012

Abstract

The global offshore oil and gas industry is constantly challenged with complex operational activities, increasing uncertainties, strict regulations and delicate health, safety and environmental issues. That has made offshore deepwater drilling operation the most time sensitive activity in the upstream oil and gas industry with high probabilities of cost and time overrun. Unfortunately, the current cost estimation models are not robust enough to deal with the multi-variables associated with cost overrun in the offshore deepwater drilling industry in the Sub-Sahara Africa. This study therefore developed a mathematical model that can give accurate estimations with limited data, precisely capture risk elements and factor probability results of all the possible cost variables in the offshore deep-water drilling operations. The study combined Bayesian approach with Activity-based costing (ABC) model to address the limitations of most existing models using primary data collected and secondary data extrapolated from past literatures, published official drilling data and companies' financial and operational reports. The integrated model showed promising results when tested against three offshore fields' data across three different countries (Erha-Nigeria, Jubilee-Ghana and Luanda-Angola). Findings from the analysis of the three fields showed cost estimates to be 10% more accurate than the estimates from existing cost estimation models in Sub-Sahara Africa. Further analysis also demonstrated the ability of the model to reduce the regional cost overrun from about 40% to 20%, thereby underlining the efficacy of the model in estimating offshore drilling cost. The strengths, weaknesses as well as the implications of using the model were also discussed. Additionally, the study developed an improved elicitation framework and

guidelines to help facilitate cost estimation in the offshore deep-water drilling operations based on the Bayesian approach. The developed elicitation process was used to collect the primary data for this work and generated probabilistic response on the known unknowns and unknown unknowns’ variables in the oil and gas industry. Finally, the research analysed and produced findings on cost reduction techniques for the offshore drilling industry.

List of Abbreviations

ABC	Activity Based Costing
ACE &AGC	American Consulting Engineers Council and Associated General Contractors
AT	Activity Time
API	America Petroleum Institute
BOEM	Bureau of Ocean Energy Management
BOP	Blow-Out Preventer
BP	British Petroleum
CII	Construction Industry Institute
CSE	Concept Safety Evaluation
CwD	Casing-while-Drilling
DAC	Drill Activity Cost
FDC	Final Drilling Cost
FPSO	Floating Production Storage Offloading
HOF	Human and Organizational Factors
HSE	Health, safety and environmental

IEA	International Energy Administration
IEA	International Energy Agency
IHS	Information Handling Services
IMF	International Monetary Fund (IMF
KPMG	Klynveld Peat Marwick Goerdeler
NCS	Norwegian Continental Shelf
NGT	Nominal Group Technique
NORSOK	Norsk Sokkels Konkuranseposisjon
NPD	Norwegian Petroleum Directorate
OC	Overhead Cost
PCD	Pilot commercial development
PSA	Probabilistic Safety Assessment
QRA	Quantitative Risk Analysis
RIF	Risk Influence Factors
SBM	Synthetic-based mud
SEC	Security and Exchange Commission
TAC	Total Activity Cost
TRA	Total Risk Analysis
USD	United States Dollar

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Research Training

Teaching and supervision

1. Facilitated in the teaching of Quality, Reliability and Maintenance module at the department of WMG, University of Warwick.
2. Successfully supervised one master's dissertation
3. Organised seminars and tutorials for masters and undergraduate students in the department of Warwick Manufacturing Group (WMG).
4. Awarded Postgraduate Diploma in higher learning and teaching in UK
5. Associate Fellow of National Education Academy

Research Student Skills Programme/ Workshops

1. Bayesian Statistics Training. Online training-2015
2. Research Ethics Module- Warwick University (Department of WMG)- 2013
3. Problem Solving Statistics- Warwick University (Department of WMG Module)- 2013
4. Cost Estimation techniques for complex projects workshop-Association of Cost Engineers UK (ACostE), June 2013
5. Leadership Seminar -Wolfson Research exchange- building leadership capacity for future business, roles and positions and taking responsibilities-2013
6. Be enterprising in your research- how to sell your research ideas and results-2013
7. Energy and Environmental special interest group (SIG)-2013

8. Speed reading - grasping more words within limited time-2013
9. Effective Applications and CVs Maths, Stats, WMG and Engineering students-2013
10. Commercial Awareness & Business Etiquette-2013
11. Making progress for 2nd year postgraduates at University of Warwick-2013
12. E-portfolio-2013
13. Envisioning and Enabling Innovation 2012-focus was on building and developing ideas-2012
14. Research Methodology Module-Warwick University (Department of WMG)-2012
15. Communicating Science to different Audiences-how to present your research to the global word with minimum technicalities yet not losing the salient content-2012
16. Knowledge and Assets Based Management KABM-2012
17. PhD Employer Networking Event- focus was to discover what employers expect from graduates-2012
18. PhD & EngD Conference for WMG- 2012

Chapter One

INTRODUCTION

1.1 Introduction to the study

To discover and produce oil and gas, holes are drilled into the Earth's crust in order to examine properties of geologic formations. Holes made by drilling are called wells which subsequently produce underground fluids such as oil and natural gas (Baker 1979, API 2006 and Kaiser 2009). The target for drilling any hydrocarbon well from an economic point of view is to make a hole in the quickest possible way, subject to technological, operational, quality, environmental, and safety constraints connected with the drilling process (Kaiser 2009). Drilling operations are risky, complex, and labour intensive; and while few of the duties are automated, a majority of the job activities are performed manually (Kaiser 2009, and Schlumberger 2015). Drilling activity is a 24 hour a day work, seven days a week and is typically carried out all seasons (America Petroleum Institute (API) 2006). Demographics and location of a field mostly determine which rig to use; i.e. whether drillship, jack up or semi-submersible drilling rig (Kaiser and Snyder 2013). Typically, shallow waters (water depths less than 400m) fields would use jack up rigs Varquez *et al.* (2005), drill ships or Floating Production Storage Offloading (FPSO) for deep-water (water depths greater than 1000m but less than 5000m) Halkyard (2005), while ultra-deep water (water depth more than 5000m) fields may opt for drillship or semi-submersible depending on the conditions of the location (ExxonMobil 1995). Fields conditions can adversely affect drilling and in extreme cases cause a complete shutdown of operations (Huaiyin 2011, and Kaiser and Snyder 2013).

The possibility of shutdowns due to extreme weather conditions and the average of more than 10% increase in the cost of drill ships hiring for the last decade make offshore drilling an expensive venture and therefore necessitate the need for cost control at all times. While drilling operations onshore (land) are less risky and costly, offshore deep-water drilling requires a floating or bottom-supported rig to conduct operations in more complex and risky conditions which in turn makes it more expensive (API 2007, Zhen *et al.* 2010, and Huaiyin 2011). In terms of rig and facility functionality, offshore deep-water operations and land operations (onshore) are quite similar (Kaiser 2009). However, the remote locations, offshore environment, some specified logistical requirements make the cost of offshore deep-water drilling higher than that of onshore for similar well depth (Kaiser 2009). America Petroleum Institute (API) reported in 2006 that the average offshore well drilled in the United States of America was about four times as costly as the average onshore well with similar well depths (API 2007 & 2016). It can therefore be inferred that, offshore deep-water drilling requires huge capital expenditures to drill, with drilling rig rates ranging from \$50,000 to \$500,000 (API 2007) and sometimes as high as \$700,000 per day (IHS 2015) depending on the rig type, water depth, market conditions and offshore basin. Aside the cost to rent a drill rig, there are other auxiliary costs such as helicopter services, standby boats, catering and other drilling supporting services costs associated with drilling an offhsore well (Osmundsen & Sorenes 2008). Dayrate (daily price to lease a rig) which only covers the use of the rig and its crew members represents 30-50% of the total cost to drill an offshore well (Osmundsen & Sorenes 2008).

Again, labour costs, materials and equipment when factored into the cost to drill and equip a well is approximately twice the rig dayrate (Donglin *et al*. 2012). Consequently, an offshore deep-water well that takes 30days with $250,000/dayrate jackup rig would be expected to cost around $15million, while semi-submersible rig with $400,000/dayrate would cost about $24million and a drillship with $550,000/dayrate about $33million to complete the well (Kaiser and Snyder 2015). Even though the physics of drilling is the same everywhere in the world, wells vary considerably in complexity and type which makes some wells more expensive than others to drill and complete.

Since 1950, more than 520,000 offshore wells have been drilled globally and more than half of these wells overrun their costs (ExxonMobil 1995, Bureau of Ocean Energy Management (BOEM) 2007, and Douglas-Westwood 2009 and 2016). In the last decade, approximately 4500 offshore wells were drilled each year and the average cost overrun was more than 40% globally (Douglas-Westwood 2016). Presently, 30 countries are engaged in offshore oil production which represents one-third of daily global oil production and concerns have been raised on the immediate need to reduce project cost overrun (International Energy Agency (IEA) 2014). The big four deep-water producers in the world are Brazil, the US Gulf, Angola and Nigeria. Current projections by IEA put West Africa as the driving force for major offshore deep-water discoveries but the rate of offshore drilling cost overrun poses a threat to future oil and gas discoveries and therefore requires urgent attention (IEA 2014). Specifically, according to British Petroleum (BP) statistical services, IEA forecasts and Quest Offshore on offshore deep-water projections put Africa and particularly West Africa countries such as Angola, Nigeria, Equatorial Guinea and Ghana as key locations for massive discoveries (BP 2010, and IEA 2014). Figure 1-1 below shows that Africa

(West Africa) tops with 24billion barrels of found oil reserves and 40billion barrels of yet to be found oil reserves. North America (US, Gulf of Mexico) and South America (Brazil) regions are equally significant for future offshore oil productions (IEA 2014).

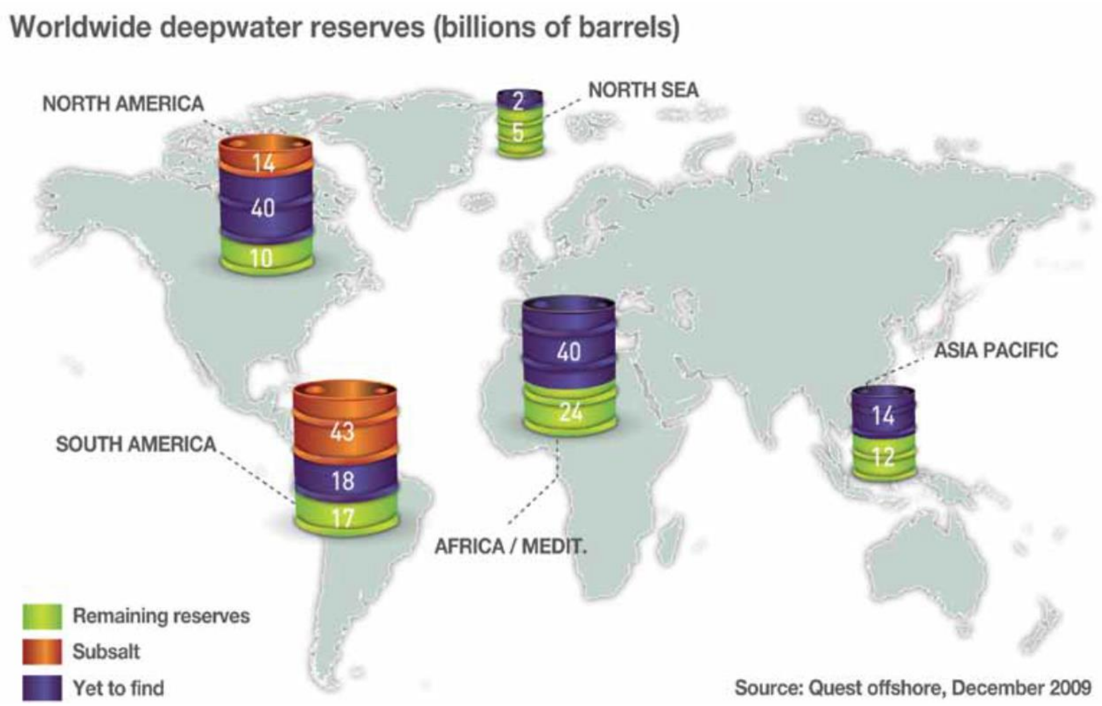


Figure 1-1: Worldwide deep-water reserves (billions of barrels) (Quest offshore 2009)

Thus, while North America offshore fields appear to be aging, West Africa offshore fields pose as new discoveries with great potentials (IEA 2014). Undoubtedly, offshore deep-water drilling activities would thrive at least in the next 20-30 years in West African waters (Donglin *et al.* 2012, and IEA 2014). In light of this, it therefore becomes critical to manage and control the perennial cost overruns in offshore drilling activities in West Africa to be able to maximise the profit of potential operators and drilling contractors.

Evaluating offshore deep-water drilling cost performance requires a critical assessment of the possible factors that affect drilling operations and quantifying the impacts of those factors on oil and gas operations (Kim & Dornfeld 2001, Amenta 2008, and Kaiser & Snyder 2013). Amenta (2008), in analysing the performance of offshore deep-water drilling suggested that operators and drilling contractors must strive to identify and eliminate non-productive time such as freeing stuck pipe, fishing, equipment repairs and waiting on weather. Cost estimation is not usually made outside a small subset of wells because of the high level of uncertainty in operating environment, the challenging processes involves, the impact of technology on drilling and many other unforeseen factors that can influence operations (Kaiser 2009, and Kaiser & Snyder 2013). Considering the level of uncertainty and ambiguity associated with offshore drilling operations, it therefore seems appropriate to examine how all these drilling cost factors can be estimated or predicted accurately to achieve efficient project cost time performance both now and in the future.

1.2 Background of research

The search for solution to control project cost overrun is an old agenda for almost every industry (Kharbanda *et al.* 1980). According to Cooper & Robert (1998), the primary goal of cost estimation is to avoid cost overruns and to ensure all projects are completed within the stipulated time and budget without any form of compromise on quality. However, the issue of cost overrun in projects is one of the serious threats businesses are confronted with in this era of extreme competition for market dominance and profitability (Cooper & Robert 1998). Cost control satisfies the basic economic principle of businesses which is "to minimise cost and maximise profits" at all times (Cooper & Robert 1998, Jergeas 2008, Claudia 2012, and Mohammad 2012). Though causes of cost overrun vary from industry to industry, their effects tend to be similar. The loss of profit, reduction in shares price, increase in prices for products and service deliveries are just some of the consequences that could result from cost overrun in a business (Anthony & Vijay 1997, Emhjellen *et al.* 2002, Jergeas 2008, Claudia 2012, and Mohammad 2012). Accounts of cost overruns are many from different industries and businesses. In the railway and highway industry, for example, a Korean Train Express 412kilometers project more than tripled its initial cost estimate of $5.2billion in 1998 to $18.4billion in 2004 when the project completed (Mansfield *et al.* 1994 and Han *et al.* 2009). In the construction industry, the average overrun globally is more than 50% (Flyvbjerg *et al.* 2002, and Priemus *et al.* 2008). Public and government projects are also not immune to cost overruns. Sambasivan & Soon (2007), reported that overruns of public projects in Malaysia are more than 100%. Investigation on cost overrun claims of Public projects in Jordan revealed that on average 80% to 90% of public projects overrun their cost (Marzouk *et al*. 2008). Global defence industry reportedly has a cost overrun of more than 30% per project (Government Accountability Office 2015), while that of National Aeronautics and Space Administration (NASA) was shown to have exceeded 60% (NASA 2014). Geographically, the average project cost overrun figures in the world is more than 60% with the highest reported to be in Middle East (89%), followed by Asia-Pacific (68%), Africa (67%), North America (58%), Latin America (57%) and Europe (53%) (Ernest & Young 2014). These findings point to the fact that no industry, business or country is insulated against cost overrun.

Kharbanda *et al.* (1980) reviewed a range of companies and found that cost control is not exclusive to particular industries or companies but a phenomenon that must be embraced by all industries and companies regardless of the size, location or capital base. In a seemingly similar but contrasted opinion, Mohammad (2012) revealed three domains that must accept and adopt cost control as a way of operation. The author categorised oil and gas sector as the forerunners of cost control ahead of any other industries because of the huge funding it attracts. Following the oil and gas sector are sectors with long execution path and high cost such as highways and railways, and lastly are government or public projects (Mohammad 2012). The consequences of inaccurate cost estimates do not only result in cost overrun but can also lead to the selection of wrong contractors which has the possibility of affecting funding of other projects (McMillan 1992, and Emhjellen *et al.* 2002). Evidence from past reviewed offshore drilling projects reveals cases of cost overrun and their threats to the oil and gas industry (Emhjellen *et al.* 2002).

Analysis of the Norwegian petroleum industry operation in the 1990s showed unprecedented cost overruns of $4billion in its offshore deep-water drilling projects forcing top management to establish a committee to probe into the overruns. The Norsk Sokkels Konkuranseposisjon (NORSOK) which was the process used to trace the root causes of the overrun revealed poor technical definition, underestimation of scope and lack of adequate risk capture among other things (Olsen and Osmundsen 2000). The report from the NORSOK process concluded that reliance on cost models that are deficient in probability and lacked experiential (expert) knowledge (NOU 1999, and Olsen, and Osmundsen 2000) will always provide misleading cost results which would consequently cause project time and cost to overrun in the oil and gas industry (Emhjellen et al 2002). Knight (1998) conducted an investigation into the Gulf of Mexico operations of BP Amoco and Exxon Mobil between 1990 and 1998 and showed consistent costs overruns between these periods as a result of lack of data at the time of estimation. The above evidence suggests that future cost models should aim to capture risks more effectively, conduct probability analysis on cost elements and equally give accurate estimate even amidst limited data.

The inability to represent project risk and uncertainty in models and the inapplicability of some cost models to operational systems were also found to play a significant role in the time and cost overruns in the mega oil sands projects in Alberta, Canada (Jergeas 2008). These claims emerged after a three-year examination of three major fields leading to the conclusion that cost estimation methods that lack robust risk identification and efficient allocation of probability to cost variables are not good enough for the oil and gas industry (Jergeas 2008). In as much as the findings by Jergeas can be said to be insightful, there is little evidence in the literature that indicates the incorporation of all the findings into a single model. It can be admitted however that there are traces of partial implementation of the findings by Jergeas in some cost models which is discussed in detailed in Chapter 4 of this thesis. Sepehri (2006), attributed the delays in projects in most developing countries using Iran as a case study to Activity Based Costing (ABC) which observes overheads of project activities in related projects to create a cost estimates for future purposes. Sepehri reported that the time and cost overruns in the case of Iran was due to poor risk and project scope capture by the model used for the cost estimation. Findings by both Sepehri and Jergeas regarding oil sands projects in Alberta point to a common theme suggesting that the inability of cost models to capture risk and assess the impact of the probabilities of each variable on cost is what mostly contributes to time and cost overruns (Sepehri 2006 and Jergeas 2008).

Moreover, Petrobras (National Oil Company of Brazil) awarded a 100 well drilling contract for its offshore projects and witnessed an overrun cost of $16billion from a projected cost of $125.8billion owing to project delays and legal issues (Millard 2012).

Initial investigations revealed that due diligence was not ensured in awarding the contracts since estimates failed to capture important risk factors that eventually led to the cost overrun (Millard 2012). Further analysis of the existing cost estimation model used by the company for the past decades showed consistent overruns which were partly caused by the lack of rigorous capture of risk and poor assessment of probability impacts on projects. Reports of several projects in the Canadian oil-sand industry having an overrun cost of over 50% and 100% (Claudia 2012) call for a more robust model that can deal with the many problems of cost overrun discussed in this section. Similar to the causes of overrun discussed by Claudia, offshore deep water drilling operations in Ghana, Nigeria and Angola in the Sub-Saharan Africa recorded a cost overrun of more than an average of 40% of project budget (IEA 2014 & 2016) which has the potential to reduce investments for new projects. Specifically, Tullow Oil the main operator of the Jubilee field in Ghana reported on its website (Tullow 2014) that, from 2007 to mid- 2011 (3.5years) a total of £10 billion was invested in drilling 16 wells in the Jubilee field with overrun percentage of more than 35%. Annual reports by Tullow revealed that underestimation of risk and poor selection of tenders/contractors accounted largely for this overrun (Tullow 2012). With Tullow and its partner's intending to invest $2.2billion into offshore drilling alone in 2016/17 and another $10billion in 2018/2019, it is feared that these projects might experience the same 35% cost overrun or even more given the organization's current knowhow (Tullow 2014). Similar to investment projections of Tullow, other instances on cases of cost overrun discussed above e.g. Jergeas (2008) on Canada, Mohammed (2012) on Africa, Millard (2012) on Brazil, IEA (2014), Shell (2014) on Nigeria, ExxonMobil on Angola all underline the importance of finding lasting solution to the menace of cost overrun. Bridging this knowledge gap i.e. investigating into the causes of offshore drilling cost overrun as well as identifying the best estimation technique required to reduce cost overrun now appear more urgent and crucial than before, hence one of the motivations for this study.

Although various kinds of cost estimation techniques and models have been developed in the oil and gas industry to improve the accuracy of cost estimates but the problem of cost overrun still persist (Wang 2004, Chou *et al.* 2006, Naizi *et al*. 2006, PMI 2008, Chou 2009, Millard 2012, and Claudia 2012). Different kinds of statistical models, mathematical equations and other forms of estimations have been explored by many oil operators and researchers yet cost overrun remains a common occurrence in every project executed in the oil and gas industry (Humphreys 1991, Clark & Lorenzoni 1985, Millard 2012, and Claudia 2012). Attempts have been made to develop various software that can predict costs in the oil and gas industry. Paul (2000), examined the contribution of cost estimations software on operator's decision making on tenders and consequently the impact it has on cost overrun in the offshore drilling operations. Using a case study of 100 projects the author assessed the potency of the software to accurately predict costs and time and concluded cost estimation software has failed to predict cost and time correctly. This is because the models or equations used for such software in themselves are not able to produce accurate cost estimates (Paul 2000). The results of a software and its reliability can be challenged if the model/theory on which it is built lack the ability to measure probability and risk levels of variables. The rigidity in existing models and other cost control decision support systems has led scholars such as Niazi *et al.* (2006), Idrus *et al.* (2011), and Gracia-Crespo *et al.* (2011) to advocate for models that are based on expert judgement in the oil and gas industry because of the lack of adequate data to overcome the limitations of current models.

The question then is; is the problem of cost overrun as a result of wrong model technique selection or is it down to poor integration of model to the systems and operations of the oil industry? Different views have been expressed and justifications given as to why different types of cost estimation techniques are appropriate to reduce cost overrun as discussed in sections 4.2 and 4.3 of this research. One common ground shared by most of the cost estimation models reviewed is that one cost estimation technique is not sufficient to eliminate offshore drilling cost overrun. Prior research has emphasized the need to harness experiences during model formulation in order to adapt lessons from previous projects when making estimates (Roy 2003, Naizi *et al*. 2006, and Ben-Arieh 2008). Consequently, analysis of the strengths and weaknesses in the current cost estimation models in the offshore drilling as critically discussed in chapter 4 and in table 4-2 in particular showed that the research gap is the unavailability of a validated framework that can precisely capture risk and factor probability results of all the cost variables in offshore deep-water drilling operations in a model. Therefore, this study investigates the appropriateness of combining Bayesian approach with a cost model in solving the problem of cost overrun in the offshore deepwater drilling industry. This approach was considered most appropriate because Bayesian method, one of the expert judgement techniques, has the ability to generate better results with limited data as demonstrated in previous studies. For example, Lecklin *et al.* (2011) found that biological effects of oil spill caused by accidents was 20% higher in Finland using Bayesian. Silver and Costa (2012) developed a Bayesian cost model in Seoul using expert judgement, while Eggstaff *et al.* (2013) showed that Bayesian method is an effective method to reduce cost overrun through their review of current models. Bayesian is generally suitable and applicable to the system and operations of the offshore drilling industry, it provides probabilistic figures using Bayes rule/theorem and offers learning opportunity which are considered necessary in building a cost model for the oil industry (Khatibisepehr *et al.* 2013).

1.3 Statement of the research question

Formulation of a research problem determines the question to be addressed. The problem statement is one step that is very important since it directs the choice of data selection, model variables and the method for the analysis (Chatterjee & Hadi 2012). It can be suggested from the above statement that a poorly phrased or wrong question formulated would eventually lead to wrong choice of response. The research question for this study therefore is: how can cost overrun in the offshore deepwater drilling industry be reduced? The study answers this question and achieves the objectives of the study through these five fundamental questions below.

- ✓ What are the causes of offshore deepwater drilling cost overruns?
- ✓ How do you evaluate and analyse the critical cost factors in the Sub-Sahara Africa offshore deepwater operations and identify the extent they contribute to cost overrun?
- ✓ Why is a Bayesian approach an appropriate solution to cost overrun in the offshore deepwater drilling sector?
- ✓ How appropriate is the option of combining a Bayesian approach with a cost model is to solving the problem of cost overrun in the offshore deepwater drilling industry?
- ✓ How can cost overrun be reduced?

1.4 Research scope and justification

The Sub-Sahara Africa offshore deepwater drilling industry has accounted for more than \$200billion investment in the last decade out of which a little over \$100billion has been spent between 2011 and 2013 alone (IEA 2014). Angola, Nigeria and Ghana received more than 60% of the investment and future projects suggest a similar trend (IEA 2014). However, cases of cost overrun discussed in section 1.2 showed a worrying trend of drilling cost overrun in Nigeria, Angola and Ghana. Aside the fact that these countries attract mega investment because of the huge oil and gas reserves they possess, their dependence on their oil reserves for economic survival equally support the need to find solution to the problem of cost overrun (IEA 2014, IMF 2014, and World Bank 2015). The scope of this study is limited to offshore deepwater drilling sector in the Sub-Saharan Africa with special emphasis on oil producing countries such as Ghana, Nigeria and Angola. These countries were chosen because of past investments made and more than $3billion USD predicted future investments to be made in the next decade (Tullow 2014, Shell 2014, and ExxonMobil 2014).

Again, the impact of recent events such as production of shale oil in the USA and the consistent decline of global oil prices are further evidence supporting the relevance of this research and the chosen scope. According to Financial Times (2016), USA which is the highest consumer and producer of oil has over 60% of its viable crude oil in shale with has an average cost 30-40% lesser than oil from North Sea and deep waters off West Africa and the sub-Sahara. It was argued that the only option producers in these producing areas have is to cut costs if they are to remain competitive. Again, the drop in the oil prices to an average of below $50 from 2014 till the end of 2016 has made the prospects of shale more viable than exploring in deep waters where cost is twice and in extreme cases thrice the cost of shale exploration. It is clear from the ongoing discussion that, the operators in this scope of study require urgent solution to cost overrun as a result of the growing interest in shale production in USA, UK and other parts of the world coupled with the fall in oil prices. Furthermore, the increasing pressure on oil companies to adopt cost effective means of exploring for crude oil and to reduce cost overrun justifies the necessity of this study and positions the research within a wider perspective.

1.5 Aim and objectives of the study

In accordance to the scope described above, the study aims at formulating a cost estimation model using offshore drilling factors to improve project cost estimation and reduce cost overrun in the offshore deepwater drilling industry.

In achieving this broad aim, the study specifically pursues these objectives.

- ✓ To identify the causes of cost overrun in the Sub-Sahara Africa offshore using past published peer reviewed journals and reports.
- ✓ To examine the limitations of current cost models in the Sub-Sahara Africa offshore
- ✓ To investigate how appropriate, the option of combining Bayesian approach with a cost model is to solving the problem of cost overrun in the offshore deepwater drilling industry in Sub-Sahara Africa.
- ✓ To analyse cost reduction techniques in the offshore drilling sector

1.6 Justification of Bayesian approach

There are a number of reasons why the choice of Bayesian approach is significant for this study. First, the fact that offshore deepwater drilling operations involve complex and laborious activities spanning several skills and fields of expertise which are required to be factored in models (Khatibisepehr *et al.* 2013) require a technique that uses existing estimates (prior knowledge) and elicited probability responses from the prior to generate a new knowledge or new estimate (posterior) which is principal to

Bayesian approach. Secondly, Bayesian offers opportunity for learning and review before final estimate is made.

Another reason why the choice of Bayesian approach is justified is because of its ability to generate realistic cost estimates through the Bayes rule (theorem) using limited data when combined with a cost model (Zhang *et al.* 1996, Bernardo 2003, Assaf *et al.* 2011, and Perez-Minana 2012). In addition to its ability to use inadequate data for predictions, Bayes Theorem can easily be adapted to the operational systems of the offshore drilling industry (Lecklin *et al*. 2011) which justifies its applicability and suitability. In addition to these, it is also simple to use and does not require any specialised training before usage. This saves time and cost for oil operators compared to buying cost estimation software in addition to the cost of training that accompanies it (Lecklin *et al.* 2011).

1.7 Definition of key concepts

Given that the meaning of most words and concepts can be relative and hence can be contested, this section provides the "operational definitions" of key concepts as used in this study.

Existing definitions

1.7.1 Offshore deepwater

Offshore deep-water drilling operations in the contest of this research refers to drilling in water depths greater than 1000m but less than 5000m which normally requires the services of drill ships or Floating Production Storage Offloading (FPSO's) (Halkyard 2005, Kaiser and Snyder 2013).

1.7.2 Known knowns

Known knowns are defined as the measurable factors that are determined prior to cost estimation (Kaiser 2009). The factors are regarded as the fixed cost and possess little or no threat to cost overrun. They are the physical characteristics of the well, geology and drilling parameters and the rig rates which are agreed in the futures market.

1.7.3 Known unknowns

The known unknowns are the cost variables that are closely linked to offshore drilling operation and cannot be quantified fully due to high risk and inherent uncertainties. Poor project management relating to site management and drilling planning, delays in procurement, decision making and project execution, and exogenous factors such as poor weather conditions, mechanical failures, impact of volatile inflation and currency depreciation against the dollar are some of the cost drivers that cannot fully be quantified but yet have direct impact on cost overrun.

1.7.4 Unknown unknowns

Unknown unknowns are the factors that are unknown in terms of how, when, and why they would occur and are represented by the project allowance or contingency budget in cost estimates. This is commonly meant to capture things that have no data, trend or traces of happening yet require budgeting for.

1.7.5 Casing

Casing is the act of using cement during drilling process to prevent contamination of fresh water well zones, seal of high pressure zones, prevent fluid loss and sticks unstable upper formation and strings together to avoid blowout of gas and other unwanted chemicals to the water zone (API 2007).

1.7.6 Pore pressure

The pressure of fluids within the pores of a reservoir, usually hydrostatic (Schlumberger 2015)

1.7.7 Day rate (drilling)

"In oil production, a day rate is the amount a drilling contractor gets paid by the oil company for a day of operating a drilling rig" (IHS 2015).

1.7.8 Casing-while-drilling (CwD)

Casing-while-drilling (CwD) as a way to reduce the problems that come with casing after drilling.

1.8 Contribution to knowledge

The current practice and current state of art in offshore drilling cost estimation has consistently shown poor coverage of known unknown factors (critical factors) which are the cost drivers of every drilling project. Therefore, the novelty and contribution of knowledge is gained through the modelling of the critical factors (known unknowns) of offshore deepwater drilling cost overrun using Bayesian Network techniques and integrating the model with Activity Based Costing (ABC) estimation method to improve cost estimation. In addition, the thesis contributes to existing knowledge by showing that the combination of Bayesian Network approach and ABC can provide a more robust and interactive cost estimation system or process for the offshore drilling industry. Moreover, the study developed an improved elicitation process which provides a more robust way of selecting experts, asking questions and collating responses in a probabilistic format using knowledge from Bayes Theorem. The study further contributes to knowledge by analysing cost reduction techniques relevant to the offshore industry using evidence from primary data collected and past findings in the literature. Finally, the study showed that the use of expert judgement elicitation is one approach that cannot be overlooked in cost estimation models if cost overrun is to be eliminated or reduced in the offshore deepwater drilling industry.

1.9 Structure of the thesis

The thesis is divided into ten chapters. Chapter 1 gives a background for the study and introduces the research problem. It justifies why the choice of Bayesian approach as appropriate model method and Nigeria, Angola, and Ghana as suitable scope for this study is significant. The chapter also presents the aims of the research and defines the key concepts used in the study.

Chapter 2 presents literature on the causes of cost overrun by describing the characteristics of offshore deep-water drilling operations, methods and process. The review covered offshore deep-water drilling factors such as; well characteristics, formation evaluation, site characteristics, drilling characteristics, geologic conditions, observable and non-observable factors and any undesirable event that can affect the total time and cost and portrays the importance of applying robustness-increasing measures. It also gives a brief overview of operations in the offshore deepwater drilling industry.

Chapter 3 discusses general models and modelling techniques. Understanding what a model is, the types and its importance were scrutinised. Again, requirements of modelling and the need for relevant assumptions were discussed whiles the different selection process of models were analysed. Specific considerations essential for formulating cost models for the offshore deepwater drilling industry were reviewed.

Chapter 4 reviews and evaluates past existing cost models and establishes the need to build a validated cost estimation model that can elicit expert responses on the known unknown variables using probability for the purposes of estimation. It further justifies why the choice of Bayesian and ABC techniques is appropriate in context to the research problem.

Chapter 5 discusses the current practices of the adopted model technique (Bayesian Network approach). Moreover, analysis of the current elicitation process was examined and the researcher proposed an improved elicitation process for cost estimation. This was successfully piloted and used in collecting primary data for this study and is therefore part of the researcher's contribution to knowledge.

Chapter 6 explains and justifies the methodology for the study. The chapter also discusses and justifies the methods used for the collection and analysis of data and lists some of the limitations of the study.

Chapter 7 presents the research model formulated and discusses how the model was validated and verified.

Chapter 8 reports on the model results and research discussions. It compares the old and the new model based on their results and variations and demonstrates why the new model is better than the current estimation models in the oil and gas industry.

Chapter 9 presents analysis of cost reduction using the developed model and findings from the primary data collected.

Finally, chapter 10 summarises the core research findings and the conclusions drawn from them. It also outlines recommendations for future research and the need for efficient operation in the oil and gas industry and other related industries.

1.10 Chapter summary

This chapter presented cost overrun as the main phenomenon of inquiry and identified it in the offshore drilling industry. The research gap identified was the lack of a validated framework that can give accurate estimations with limited data. For example, a model that can precisely capture risk, factor in probability results of all the cost variables in the offshore deep-water drilling operations and be suitable and applicable to the systems and operations of the industry. The gap formed the main research aim and led to the formulation of the research questions and study objectives. Based on the research problem, the researcher was motivated to investigate the prospects of combining Bayesian approach with a cost model to address the research gap and problem. An account of the contributions of this research were given and the content of each chapter was explained. Detailed analysis of the causes of cost overrun in the offshore deepwater drilling industry is discussed and examined in the next chapter (two).

Chapter Two

OVERVIEW OF OFFSHORE DRILLING OPERATIONS AND CAUSES OF COST OVERRUN

2.1 Overview of the offshore deepwater drilling operations

Once data from geological studies and seismic surveys can confirm a hydrocarbon prospect for a field, a well is drilled to examine the economic viability of field (Smit *et al*. 2010). All drilling operations are mostly conducted to meet three basic objectives: to provide a fit for purpose well, to ensure that health, safety and environmental (HSE) work procedures are adhered to, and to minimize overall well cost (Payne *et al.* 1994). Of these objectives, cost control appears to be the most crucial as failure manage it affects project budgets, future projects investment among many others (Payne *et al.* 1994, British Petroleum 2010, and Smit *et al*. 2010). Hence proper measures and safety standards are employed in oil and gas drilling operations to achieve this crucial objective while addressing the other two mentioned. Similar to other oil and gas drilling operations, the offshore deep-water drilling has two stages of drilling. The first is running and cementing of cases while the second is drilling until the drill bit reaches the depth of the targeted zone (Payne *et al.* 1994, British Petroleum 2010, and Smit *et al*. 2010).

The two stages of drilling are somehow intertwined and overlapping in each of the stages until the final well is completed. Running a drilling operation begins with the preparation and setting up of the field with the aid of appropriate equipment such as drill ship, accommodation for crews, electricity, water and all the auxiliary items needed for successful drilling (Aven and Vinnem 2005). Offshore exploration and development wells are usually drilled from moveable offshore drilling units and depending on the water depth and remoteness of the location, these "rigs" may be jack-ups (up to 4000 feet of water), or semisubmersibles, or drill ships (up to 12,000 feet of water). Jack-ups are bottom-supported units while semisubmersibles and drill ships are floating units (Aven & Vinnem 2005, and Diamond Offshore 2014). The figure 2-1 below shows the different types of rigs that can be used for drilling activities in the offshore deep-water sector.

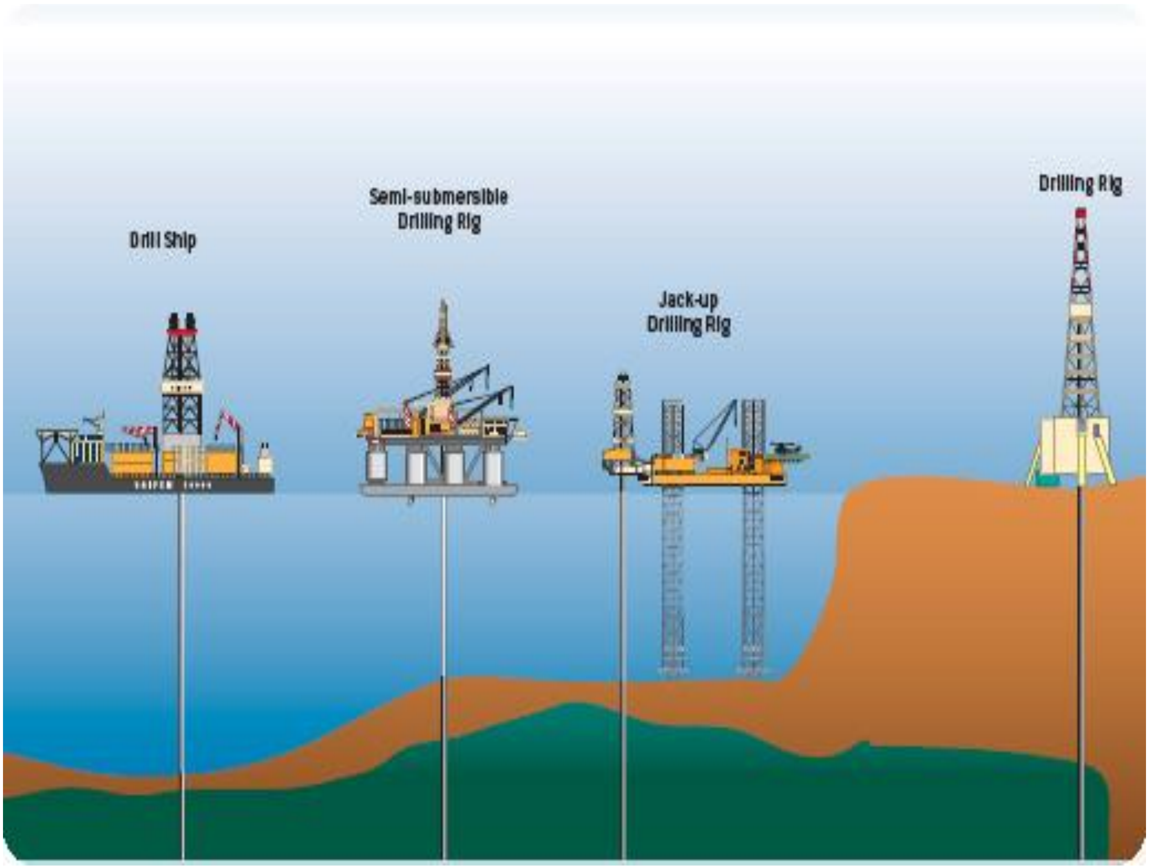


Figure 2-1: Offshore deep-water rigs **(Rondini 2010)**

When an appropriate rig is selected based on location, geology of the field and stipulated budget for the project, the drill crew immediately commence drilling by making a starter hole (Williams 2011). Drill bit, collar and drill pipe are placed in the starter hole for the actual drilling operation to begin (Williams 2011). A Blow-Out

Preventer (or "BOP") is installed on top of the casing head before drilling takes place. The BOP has high-pressure safety valves designed to seal off the well and block any escaping gases or liquids from the hole beneath in order to prevent a blow-out from occurring (Williams 2011). As drilling progresses, mud is circulated through the pipe and out of the bit to float the rock cuttings out of the hole and new joints are added to the drill pipes as the hole gets deeper. When pre-set depth is reached, casing pipe is placed in the hole for cementing to commence to avoid oil and gas leakages (DeRosa 2013). Finally, the cement is allowed to harden and then tested for such properties as hardness, alignment and a proper seal (Speight 2015). For pictorial purposes, the figure 2-2 below portrays a typical well with pipeline, casing tube and several cementing stages in an offshore deep-water drilling process.

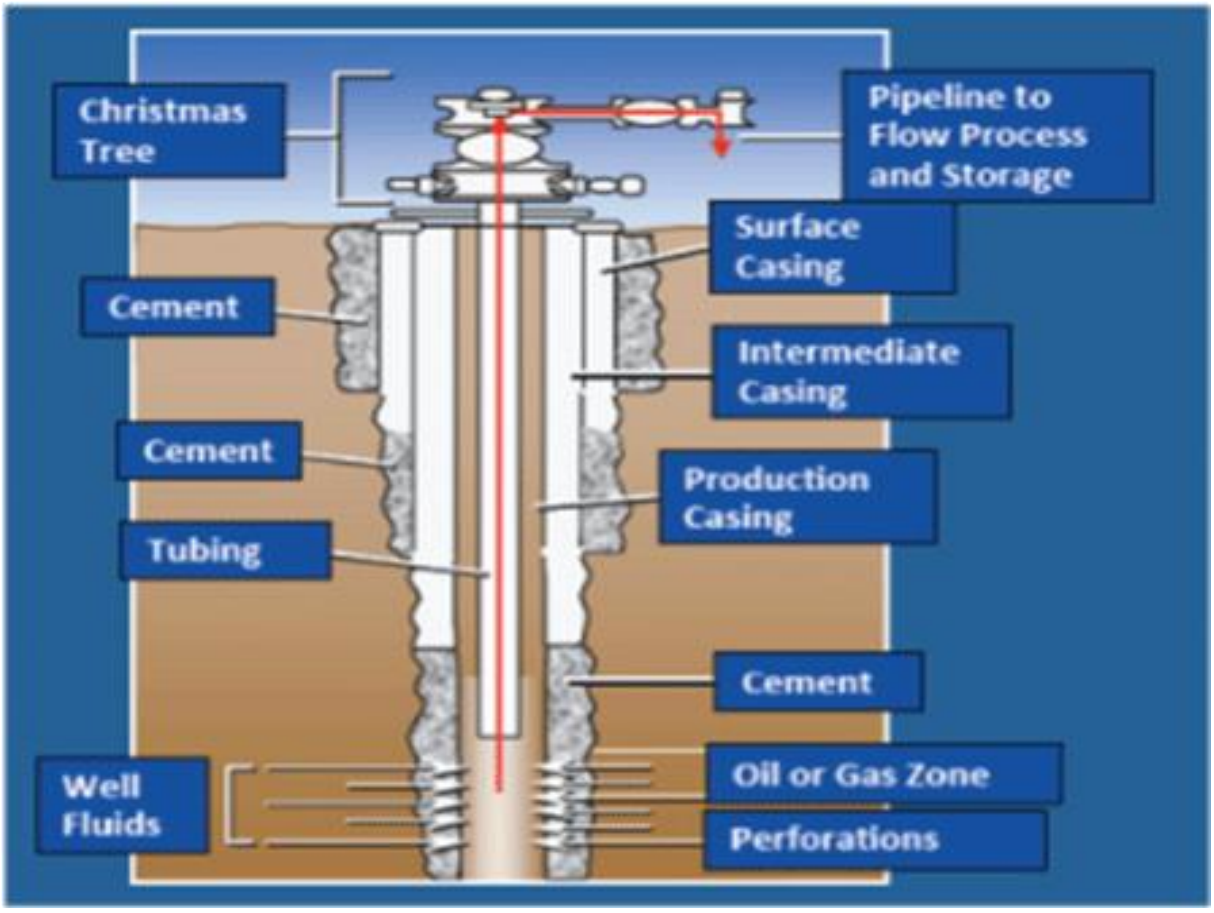


Figure 2-2: Offshore drilling process (Speight 2015).

For the drilled well to be ready for usage other important activities need to be undertaken. Such as pumping mud into the hole in order to separate all debris from plugging the well hole. Additionally, mud system equipment such as de-sanders, de-silters and de-gassers are positioned in the well hole to remove smaller particles and gas from the well (Speight 2015). Although the process involved in oil and gas drilling seems quite linear from a theoretical point of view, the increasing risk and uncertainties associate with the operations is what often result in cost overrun for most drilling projects (Abimbola *et al.* 2014, Ismail *et al.* 2014, and Speight 2015). The more operational delays there are, the more the drilling cost incurred. Most drilling rigs operate 24 hours per day, 7 days per week and rig crews' work 8 or 12-hour shifts in rotations that last anywhere from one to four weeks or more, depending on the location (Ismail *et al.* 2014). This pattern of work should be continuous without any distractions until drilling is completed as any adverse effect on the smooth running of the drill has a cost implications attached by extension.

Having discussed the offshore drilling process and highlighted some of the factors that escalate costs, it is equally vital to explain and discuss the risks that surround oil and gas operation as well. Hence the next section discusses and evaluates the different types of risks and complexities associated with offshore drilling activities. This will clearly set the stage to critically evaluate and review the past cost models and help direct the development of the validated model the research seeks to achieve. The next section on risks and complexities will help to comprehensively assess and evaluate the capabilities of past models to handle cost overruns under the given requirements and risk conditions in the offshore drilling industry and would further provide proofs of the gaps the research intents to address.

2.2 Operational risk and complexities in offshore drilling operations

Drilling for oil and natural gas is technically demanding. Pressures encountered in the rock formations need to be managed safely to ensure that hydrocarbons cannot escape from the borehole (BP 2010, Schlumberger 2015). Again, risks associated with offshore deep-water drilling operations leave huge environmental footprints and present Health and Safety issues (US National Commission 2010). After the Macondo oil spill at the Gulf of Mexico in 2010, the National Commission set up by the US government recommended a reassessment of the risks associated with the BP Deep-water Horizon Spill and Offshore Drilling activities across the oil producing regions. A proactive risk-based performance specific to wells as well as a single drilling activity were suggested to be used in all offshore drilling activity worldwide (US National Commission 2010). This ensures that relevant risks and activities that can affect the project delivery time and budget are assessed and planned for. Similar findings to the US National Commission's report in 2010 suggested that for projects to remain within budgeted cost, operators could conduct risk assessments on individual facilities, operations and environments similar to the "safety case" approach used in the North Sea (HSE 2010). The criteria used by the US National Commission have been found not to be applicable in every region due to different climatic, geological and environmental characteristics (Skogdalen and Vinnem 2011). Skogdalen and Vinnem (2011) reviewed 15 Quantitative Risk Analysis (QRA) techniques used for offshore North Sea and argued that the techniques currently used primarily focus on frequency of occurrence. None of the 15 risk analysis criteria was based on Risk Influence Factors (RIF) identified at the drilling planning stage (HSE 2006, HSE 2006, and Skogdalen and Vinnem 2011).

Also most oil project owners and drilling operators do not include Human and Organizational Factors (HOFs) which always affect the project and consequently result in cost overrun. Evidence from the Macondo blowout suggests that HOFs such as working practice, competence, communication, training, procedures and management were the root cause of the accident that has cost British Petroleum billions of dollars (US National Commission 2010, and Skogdalen & Vinnem 2011). It is therefore important that all parties involve clearly understand the level of risks and complexities that an offshore drilling activity presents so as to help make well informed cost estimates. Failure to do this will inevitably expose the drilling projects to higher cost overruns (Skogdalen & Vinnem 2011). This therefore explains why a safety case that clearly outlines potential risks and the way they intend to be managed by the risk owner (e.g. drilling company) has become mandatory (HSE 2006, Schlumberger 2015). A good safety case will undoubtedly help to reduce risks from major offshore drilling accidents as well as their impact on health and safety of workforce. However, despite the development, the use and popularity of the safety case in UK, Norway and some part of US for more than two decades, it is not yet universally accepted as the only way to address the issues of risks and safety in the offshore drilling operations (Vinnem 2007). A range of other methods seem to be used in different oil producing regions such as Probabilistic Safety Assessment (PSA), Concept Safety Evaluation (CSE), Total Risk Analysis (TRA) (Skogdalen and Vinnem 2011). Although it should be noted that irrespective of the method used, one factor remains crucial i.e. the risk assessors' ability to carefully diagnose the risks inherent in their operations.

Deepwater drilling activities encounter a high level of Risk Influence Factors (RIFs) such as uncertainty in seismic and geological factors, complex casing programs, high well pressures and temperatures, difficult rock formations and lack of experienced personnel (Wiston & McFadyen 2001, Thurmond *et al.* 2004, Shaughnessy *et al.* 2007, Salazar 2010, Rambaldi 2010, Ragan *et al.*2010, Miller *et al.* 2005, Lawrence 2000, Lane & LaBelle 2000, Close *et al.* 2008, Rich et al. 2010, Addison et al. 2010, and Noynaert & Schubert 2005). Most of the offshore deep-water fields in the Sub-Sahara Africa have water depths of over 3000meters, shut-in-pressures more than 600bars and well temperatures higher than 195 degrees Celsius (Close *et al.* 2008). Operators in the Jubilee field of Ghana such as Tullow Oil (one of the study area in the current research) therefore need to manage the complex deep-water operation as unnecessary mistakes can cost operating firms tens of millions of dollars (Rich *et al.* 2010, Addison *et al.* 2010).

Furthermore, there are risks connected to the life cycle phases of drilling both the well planning phase and the drilling phase. With both phases equally important, the plan usually includes yearly drilling tasks and provides detailed descriptions of the drilling activity and interventions (Okstad *et al.* 2009). The entire drilling activity is defined by the well plan and it specifies the target for the drilling and discusses the risks or hazards related to the drilling (Okstad *et al.* 2009). Based on the information and instructions from the well plan, the drilling activity is then undertaken. The drilling phase consists of drilling, running casing, cementing, circulation, fluid displacement, clean up and completion. Each of these activities has the potential to trigger accident and cost overrun if not properly managed. Additionally, well integrity poses a greater risk if it is uncertain (API 2006 & 2010), and three categories of offshore drilling incidents affect the “integrity” (completion) of a well. These are accidental well inflow, well leakages and blowout. Well inflow or leakage occurs when the well “kicks” in gas, oil or water as a result of instability in the well or in the event of equipment failures ((API 2006 & 2010). However, blowout is mostly managed by installing a Blowout Preventer (BOP) which helps to shut the well down if the pressure can trigger an accident (Dethlefs & Chastain 2011).

Analysis of risks in drilling operation is not only demanding but complex as well. Traditionally, risk management was focussed on technical systems and capabilities Vinnem (2007), Aven & Vinnem (2007), and Aven *et al.* (2006) but assessors have more recently extended its application to the human and organizational factors (HOFs) that engender those risks (Bea 2001). Several reports describe how HOFs can either contribute to the success or failure of a drilling operation (Salazar 2010, BP 2010, Bartlit *et al.* 2011, and Graham *et al.* 2011). The tables 2-1 and 2-2 below summarise some of the risk factors that are essential to the offshore drilling operation. Table 1 covers Human and Organization Factors (HOFs) that influence major hazard risks while Table 2-2 focuses on the Categories of risk influencing factors (Aven *et al*. 2006).

Table 2-1: Human and Organization Factors (HOFs) that influence major hazard risks (Aven *et al*. 2006, Rich et al. 2010, Addison et al. 2010 Skogdalen and Vinnem 2011,)

VARIABLES	RISK FACTORS
Work practice	The complexity of the given task, how easy it is to make mistakes, best practice/normal practice,
Competence	Training, education, both general and specific courses, system knowledge, etc.
Communication	Communication between stakeholders in the process of plan, act, check, and do

Management	Labour management, supervision, dedication to safety, clear and precise delegation of responsibilities and roles, change management.
Documentation	Data-based support systems, accessibility and quality of technical information, work permit system, safety job analysis, procedures (quality and accessibility).
Work schedule aspects	Time pressure, work load, stress, working environment, exhaustion (shift work), tools and spare parts, complexity of processes, man machine-interface, ergonomics

Table 2-2: Categories of risk influencing factors ((Aven *et al*. 2006, Rich et al. 2010, Addison et al. 2010 Skogdalen and Vinnem 2011)

VARIABLES	RISK FACTORS
1 Environmental-Surroundings Environmental risk is caused by dynamic conditions like weather and static conditions like water depth and seabed conditions. Drilling equipment and offshore workers are directly exposed to the natural environment.	– Air temperature – Water temperature – Wind (e.g. hurricanes) – Rain/Snow – Waves – Earthquake – Seabed conditions – Water depth – Sea water salt
2.Environmental-Geological risk Geological risk is caused by the complexity and uncertainty of geological	– Drilling margins – Pressure – Temperature – Sandstone

conditions. Uncertain seismic increase the geological risk.	– Flow assurance – Crack and cave – Shut In Pressure – Leak off – Lost returns – Lithological discrimination – Blowout rate
3. Facility-Technological risk Safe operations demand the necessary quality and reliability of the drilling vessel, well equipment and well control equipment. Deviation from expected quality and reliability increases technological risk.	– Instrumentation – Reliability and validity of the instrumentation – Performance of drilling fluid – Well control equipment (pump capacity, mud capacity, valves, etc.) – Power generation and emergency power supply – Blowout preventer (BOP) – Cement – Casing – Maturity of new technology
4 Operational risk The risk of loss resulting from inadequate or failed internal processes, people and systems.	– Work practice – Competence – Communication – Management – Documentation – Work schedule aspects

The relevance of the above tables to this study is the awareness they create regarding the need to assess and evaluate the cost impact of human and organization factors, and categories of risks as they form part of the primary cost factors. Hence having clearer understanding of these factors and their potential impacts on offshore drilling operations would ultimately help to trace the activities that make up these cost factors in building cost models for the industry. Findings from major offshore drilling operations in United States of America, North America, Europe, South America and some part of Africa showed that cost overruns recorded can be reduced considerably if Risk Influence Factors for individual facilities, operations and environments can be covered by cost models (Aven *et al*. 2006, Rich *et al.* 2010, Addison *et al.* 2010, and Skogdalen & Vinnem 2011).

2.3 Problem of costing and causes of cost overrun in the offshore deepwater drilling sector

The driving force of offshore drilling cost overrun is directly linked to time (Abimbola *et al.* 2014). As discussed in section 2.1; because of the sensitivity of drilling to time, any delays or breakdowns, accidents, unforeseen events and any other occurrences that have the potential to halt or stop the drilling operations automatically affect the cost element of all the factors associated with effective drilling (Abimbola *et al.* 2014). After examining 219 offshore drilling accidents and project delays for the past 56 years, Ismail *et al.* (2014) found that blowouts ("uncontrolled release of crude oil and/or natural gas from an oil well or gas well owing to failure in the pressure control systems") appeared as the highest accident causation factor with 46.1%, followed by storms and hurricanes with 15.1% and then structural failures with 11.4%. The authors also showed that offshore delays and accidents in any form will always cost the drilling operators a substantial amount of money, with the potential also to affect the payback time of the project and investments for other projects. Moreover, because of how intensive drilling operations are carried out in today's oil and gas major fields around the globe the need to find answers to cost overrun has become even more urgent (Saibi 2007, and Kaiser 2009).

In every continent and region where oil and gas is produced, the problem of cost overrun remains a growing challenge (Saibi 2007). Evidence from the works of Osmundsen (2001) on Norway in Europe, Jergeas (2008) on Canada in North America, Claudia (2012) on Brazil in South America, Marzouk *et al.* (2008) on the Asian region and IEA (2014) on Middle East and Africa all provided compelling evidence that suggests there is an increasing trend in cost overrun in offshore drilling projects with an average of more than 40%. While cost relating to onshore drilling are minimal because of several favourable factors compared to offshore drilling that is associated with more difficult conditions and environment, the cost of drilling an offshore well is more than thrice that of onshore depending on the geology of the offshore field (Saibi 2007). Again, since onshore fields are depleting with little or no prospect of discovery, the future of oil and gas supply lies with offshore fields and shale reserves which are in abundance. Therefore, the issue of cost overrun require more desperate and rigorous solution for the offshore oil and gas operation because of the high risk and investment involved in the industry (Osmundsen 2001, Saibi 2007, Jergeas 2008, Marzouk *et al.* 2008, Claudia 2012, and IEA 2014).

Since it is generally agreed that the best way to tackle a problem is to know and understand the cause, it is vital to identify and review the causes of cost overruns in the offshore deep-water drilling industry (Daniel *et al.* 2011). This would make the proposition for a validated cost model to be better substantiated. The offshore drilling operation is made up of five key departments or service providers which are rig activities, logistics, equipment and materials, drilling services and administration and management (Osmundsen *et al.* 2008 & 2009). As a practice in the industry, cost estimations are made with reference to these five departmental duties or activities (Osmundsen *et al.* 2008 & 2009). Hence, the causes of cost overrun in the offshore deepwater drilling operations are often discussed under the five departments/services as each of them contribute to cost overrun in diverse ways.

2.3.1 Cost overrun from rig factors

Knowing and understanding the characteristics of the field to be drilled is not only crucial for successful drilling, it also serves the purpose of saving significant amount of money that would have been used in experimentation (Kaiser 2009). Offshore drilling cost estimations are done using data available on the well characteristics however the ability to identify the causal factors of cost overruns from the data provided on the well features cannot be over emphasized (Kaiser 2009). As can be expected, failure to efficiently interpret and factor these well dynamics into the cost estimation can consequently result in time and cost overrun. The rig activities in the context of the offshore deepwater drilling operations are all the measureable data on the geological formations of the fields and covers predominantly the physical characteristics of the well, geology and drilling parameters (Baum *et al.* 1986, and Kaiser 2009). However, since data on the rig activities are validated and calibrated before any cost estimate is made, this activity has a lower chance of contributing to cost overrun (Kaiser 2009). Again, because this data or information about the field to be drilled is measureable before cost estimations are done they are often tagged as the "known knowns" (Kaiser 2009) and generally have limited impact on cost overrun. The next three sections evaluate factors considered under the rig activities.

2.3.1.1 Well type

The type of well to be drilled can determine the time and cost of the drilling operation. An exploratory well is one that is drilled to find oil or gas in an unproved (untested) area while a development well is a well drilled in a proven producing area to maximize the chances of success (IEA 2014). Wells drilled in areas with unproven oil and gas reserves fall in the category of exploratory wells since the intent is to add those wells or fields as reserves for the operators (Baker 1979). In the context of the well type as a cause of cost overrun, it can be argued that availability of data on the subterranean conditions and geological formation might help reduce cost if the correct decision is made using these data (Baker 1979, Baum *et al.* 1998). This is because absence of known data on the field to be drilled can result in cost overrun since the basis for any cost estimation would rarely be built on the actual well type but rather on presumed assumptions on the viability of the well (Baum *et al.* 1998). Another important determinant of the success of any well is an understanding of the well conditions, geological formation, and spotting the right angle to be drilled as failure to do these pose threats of delay and cost escalation (Baum *et al.* 1998). The cost of logistics, drilling materials, and other drilling auxiliary services are influenced to some extent by the type of well to be drilled making it essential to be have knowledge on them.

In addition to the above discussion, Brett & Millheim (1986) and Kaiser (2009) argued that there is no doubt the type of well has a greater influence on the cost of drilling as each well type has its own unique risk and peculiar drilling approach. Research by Brett & Millheim on the performance of drilling revealed that more often than not the first well drilled in any exploration activity is the most expensive because it has to be drilled with more caution. This is more so when the geologic formations and the risks have been largely untested (Brett & Millheim 1986). Knowing the type of well being budgeted for is very important if cost estimates are to be accurate (Kaiser 2009). For example, time and cost required in drilling a development well is expected to be smaller than an exploratory well for the same well for a given period since information collected during exploration is used in drilling which supports the measurability of the rig activities (Brett & Millheim 1986). Kaiser (2009) argued that suffice the same well is used for both exploratory and development, it only provides improved knowledge about the well and its challenges which cannot be translated literally into financial gain unless other evidence suggests so. The cost contributors to drilling projects are not limited to the well type but include also the cost of materials and equipment, logistics, other auxiliary services and cost of administration and project management (Kaiser 2009). Evaluation of offshore wells drilled in the Gulf of Mexico in 2006 showed that there is little or no difference in terms of cost in both exploratory and development wells hence it suggests therefore that determination of the well type on its own does not guarantee precision of cost of project (American Petroleum Institute 2001 & 2006, and Kaiser 2009).

It can however be suggested that in developing offshore drilling cost estimation models focus must be on the impact of the geologic features on the drilling activity and the type of well being drilled. Thus factors such as geologic formations, stratigraphic layers of wells, over and under pressures of the well can cause drilling time and cost overrun if they are not identified during the gathering of data on the field (American Petroleum Institute 2001 & 2006). Brett & Millheim (1986) argued that development activities are highly linked and connected to exploratory facts and information, as such in modelling cost for drilling operations prominence should be on the impact of the characteristics of well on drilling and not the type of the well. In offshore drilling operations where risks are high compared to onshore, overpressure from the well can halt drilling operations and cause delays and increase cost (American Petroleum Institute 2001 & 2006).

2.3.1.2 Well geometry

Drilling a wellbore has three-dimensional facets which are the length, diameter and the curvature of the downhole trajectory. Water depth from the waterline to the seabed can be measured with the help of the 3D features of the well before drilling activities start which helps in choosing the correct drilling rig (Liu & Samull 2008). One of the threats to precision in offshore drilling cost is the offshore water depth (Kaiser 2009). Costs, hazards and problems of offshore drilling activities increase proportionally to increase in water depth and drilled interval according to Kaiser (2009), hence prior knowledge provides operators with the opportunity to prepare against these during drilling. Evidence from a drilling activity in South-western Eugene Island (EI), in the Northern Gulf of Mexico demonstrated that the risks, cost and complexity of operations rises in depth in deep-water compared to the same activity in shallow waters (Shaughnessy *et al.* 2007, and Liu & Samull 2008). Approximately about 40% of the wells in the offshore deep-water industry are either 10000 feet or even more and with low supply of rigs that can drill in such depths, high demand of the rigs tends to push the price further which then results in cost overrun (Shaughnessy *et al.* 2007, and Liu & Samull 2008).

Kaiser (2009) discussed that drilling operations that require drill ships have to endure high cost overruns since specialised technology required to make drilling possible is in itself expensive and therefore increases the dayrate. Drilling in deep-waters also poses the risk of time overrun as more time is lost replacing drilling equipment as the well drilled gets deeper (Amenta 2008). Furthermore, extra strings (pipe that transmits drilling fluid) might be required as the depth increases which generates additional risks and further challenges that could potentially force cost to overrun (Amenta 2008). A study by Liu and Samull (2008) showed that increasing casing strings from 3 to 4 has the potential to increase cost by 10-20% and that adding 4 to 5 casing strings could cause cost to rise by 20-30%. Statistics in the offshore deep-water drilling operations has shown that the percentage of total well cost as a fraction of total well depth has a strong correlation with cost such that more than 50% of the total drilling budget can be spent on drilling the last 10-20% of the well (Kaiser 2009). Evidence from the works of Kaiser (2009) has also proved that well depth has a direct positive relationship with cost in drilling.

2.3.1.3 Drilling rig rates

The amount a drilling contractor charges for running a rig per day (rig rate) is one of the most apparent cost factors in offshore drilling. The choice of drill selected determines the rate and is normally informed by the awareness of the depth and bottom conditions of the field, its expected weather conditions, wind and tides pressures, wave heights when choosing a rig for drilling (Osmundsen *et al.* 2010). While rig factors such as rig rate arguably have little contribution to cost overrun due to the fact that its cost figures are reliably informed by prior information gathered on the field during an exploratory exercise, failure to select a rig that can function effectively under the conditions associated with the well will result in delays in drilling and extra cost burdens (Osmundsen *et al.* 2010). Osmundsen *et al.* (2010) discovered that there exists a positive relationship between drilling cost overrun, rig selection and the efficiency of the drilling personnel. Analysis of drilling efficiency (speed) with reference to the Norwegian Continental Shelf (NCS) showed a consistent cost accuracy in rig rates in cases where oil operators used available information for their cost estimation on the field in question; failure to do so on the other hand resulted in higher cost above the estimated amount. Yost *et al.* (2015) outlined the relationship that exists between rig hire and the total cost of drilling. The authors argued that selecting the rig that cannot operate within the condition of the well to be drilled can more than double or in some cases triple the cost of the drilling project.

Review of reports from the Norwegian Petroleum Directorate (NPD) showed that drilling time and cost of rig rates are reduced when enough information is known on the well to be drilled since the cost of drilling rigs hired (day rate) are generally determined by the well type, geometry, geological formation as well as other well characteristics (Osmundsen *et al.* 2010). Corts & Singh (2004) examined the rate of drilling efficiency decline from 2001 and observed that the efficiency or the speed at which wells were drilled had fallen from 102meters per day to 80 meters per day due to inadequate information on the wells drilled. It therefore appears that the delicate and complex nature of offshore drilling operations requires that appropriate information is collected with great precision if cost overrun is to be reduced or eliminated. Hence to maximise the efficiency level of rigs hired, the need to better understand the well demands and complexity of the field cannot be overemphasised as this will help to select the appropriate rig and technology that will enhance productivity (Osmundsen *et al.* 2010).

2.3.2 Equipment and materials factors as causes of cost overrun

Another potential cause of cost overrun is the inefficiency of equipment and materials to support drilling activity and machine failures. Equipment such as drilling bit and material such as drilling fluid have considerable impact on the time used in drilling. This section discusses how drill bit, drilling fluid and mechanical failures can trigger cost overrun in the offshore deep-water drilling operation (Tibbits *et al.* 2002, Kaiser 2009, and Osmundsen *et al*. 2010).

2.3.2.1 Drill bit size/type

The drill bits though a very small part of the drill machine, has the potential to cause delays or even stop the entire drilling operations and plunge drilling projects into cost overruns. This becomes inevitable if, for example, the bit used is inappropriate for the prevailing condition of the well (Tibbits *et al.* 2002). When drilling a well with different rock layers there is a need to change the drill bit for every rock layer if the bit used do not have the ability to penetrate all forms of rock layers (Tibbits *et al.* 2002). The cost problem in this case is the time lost in changing the bits at every new rock layer which also affects the fluency of drilling and increases the lag time. Tibbits *et al.* (2002) analysed several drilling bits used in drilling wells in North of Mexico and found that due to the hardness of formation, pressure regime and the drilling plan of North of Mexico offshore fields, drill bits with tricone have higher ability to withstand these challenges compared to the other types of drill bits.

Again, removal of rock particles stuck in drill bits when drilling in deepwater drilling can also cause considerable delays in the drilling activity and increase cost (Tibbits *et al.* 2002, Kaiser 2009 and Osmundsen *et al*. 2010). Analysis of delays caused by changing rig bits and tripping times (removal of waste and debris) were carried out by Osmundsen *et al.* (2010) in the North Sea Norway and by Kaiser (2009) in the Gulf of Mexico with both studies showing similar results. It was uncovered that the higher the number of tripping times during drilling the higher the delays and cost of drilling. Unfortunately, when developing a cost estimate for a drilling project, most scholars fail to factor in the potential delays that can result from changing a drill bit, removal of stacks in drill bits and other seemingly minor elements things that can halt or stop the drilling activity.

2.3.2.2 Drilling mud

The use of drilling fluids ensures faster penetration rates and increases the efficiency at which the drill machine is working (Tibbits *et al.* 2002, and Kaiser 2009). Not much has been written on the effects of drilling fluid on drilling cost overrun. Even though drilling mud tends to be playing an important role in drilling. The mud fluid controls the pressure at different depths during drilling operation. Synthetic-based muds (SBMs) help drill machines to endure more hostile downhole conditions and have higher lubricity (Kaiser 2009). It is therefore important that cost estimators are aware of the cost and time benefits of the different kinds of mud fluid in order to make appropriate cost decisions during estimations. Again, drilling fluid helps in well cleaning and drilling stability however the only problem linked to fluid usage is the shape of the well. In horizontal and multilateral wells, in particular, it becomes difficult to run mud programs which obviously delay the drilling process. Therefore, awareness of the time needed to perform these tasks and their overall cost impact cannot be ignored if cost overrun is to be tackled in the offshore deepwater drilling industry.

2.3.2.3 Mechanical failures

Failures abound in any process or operation but the ability to anticipate and make adequate plans for the effects of these failures is particularly crucial. Young *et al.* (1984) conducted a study on 435 mobile jack-up rigs and found that about 2.6% of these rigs experience mechanical failures and accidents. Although the study failed to suggest how to stop mechanical failures, it provided ample information about cost implications thereby confirming it as one of the causes of cost overrun. A further study uncovered that of all the failures and accidents that happen in offshore deepwater drilling operations, over one-third are associated with foundation problems (lack of understanding of the well formation) Hossain *et al.* (2011) hence it was suggested that to reduce the risk of foundation failure, investigation of subsurface conditions is necessary to reduce these hazards (Zheng *et al.* 2014). Recently, efforts have been made especially in the area of maintenance and pipelines reliability in the oil and gas industry to use analytical methods to review historical cases of accidents and machine failures. The use of such methods can help experts involved in cost estimation elicitation process to make more informed cost predictions using analysis from these historical cases (Shahriar *et al.* 2012, and Zheng *et al.* 2014).

2.3.3 Drilling services factors as cost overrun causes

During well drilling, there are three important services which ensure that the oil and gas reserves are kept secured for production through the hole drilled (Crockford 1975, American Petroleum Institute 2007, and Azhar *et al.* 2008). Casing geometry, casing scheme and cement logging do not only protect the crude oil but also prevent unwanted gases, chemical and debris from contaminating the environment. Evaluation of these two activities and their impacts on cost overrun are discussed below.

2.3.3.1 Casing geometry

Casing is the act of using cement during drilling process to prevent contamination of fresh water well zones, seal off high pressure zones, prevent fluid loss and sticks unstable upper formation and strings together to avoid blowout of gas and other unwanted chemicals to the water zone (American Petroleum Institute 2007). It is one of the important functions in drilling wells as without it damage to the environment and the water table could be unbearable and costly (American Petroleum Institute 2007). The cost of casing ranges from 10-20% of total drilling cost which makes it one of the drilling activities that require efficient planning and management if cost overrun is to be tackled (American Petroleum Institute, 2007). Casing plays a significant role in that it prevents collapse of the borehole during drilling and protects subsurface formation from coming into contact with bore hole fluids. It is the only known technology to date that blocks fluid and gas leakages in drilling operations (American Petroleum Institute 2007).

Well formation pressure can only be controlled during drilling with the help of casing as it creates a fluid conduit in the well (American Petroleum Institute 2007). Jenkins & Crockford (1975) analysed the drilling cost for some selected European drilling activities and observed that total drilling cost reduces if the well being drilled does not encounter any abnormal formation pore pressure. A similar study by Azhar *et al.* (2008) on five offshore drilling projects in Tanzania and Angola revealed the same outcome. Proehl (1994) examined the impact of pore pressures and any abnormal events on the total cost of drilling activities and found that deeper wells that permeate abnormal rock formations, unstable shale sections and or salt sections tend to have a direct effect on cost overrun in drilling. Despite the challenges related to casing, there have been some technological breakthroughs in place to reduce drilling costs. Tesco in 1997 tested the possibility of casing-while-drilling (CwD) as a way to reduce the problems that come with casing after drilling (Azhar *et al.* 2008). It further emphasised the benefits of having early information as it presents opportunities to make cost savings decisions (Azhar *et al.* 2008, and Enshassi *et al.* 2009).

2.3.3.2 Casing scheme

In order to protect the underground fresh water from contamination, to prevent upper rock formation caving-in during drilling, to control high-density drilling pressures and surfaces and to avoid potential blowout, having a good casing scheme becomes paramount (Rigzone 2015). Figure 2-3 below shows the different types of casing required when drilling. Surface, intermediate and production casings play a vital role in ensuring that wells are drilled and produced with minimum safety and environmental costs. Due to the high downhole (well) pressures during drilling, casing scheme are supposed to be run with high efficiency. The diagram shows that casing acts as a protective seal between the well being drilled and the rock formation hence any leakage from the casing may allow dangerous chemicals to contaminate the underground water and pressure from the well can also cause blow out.

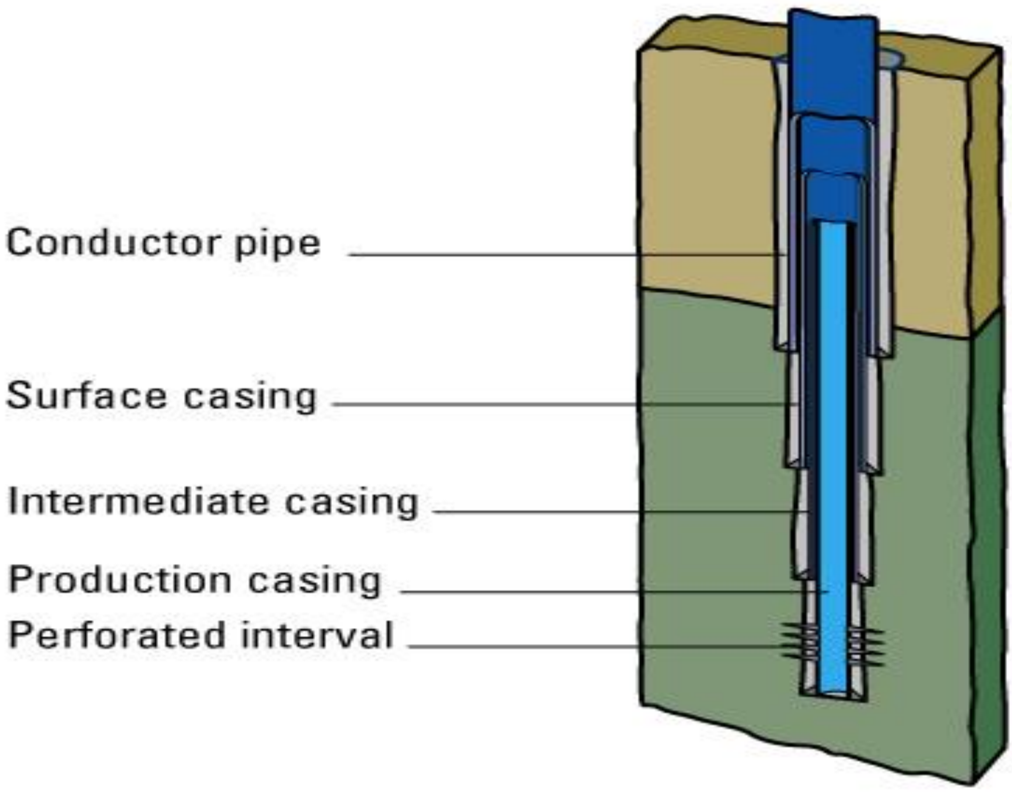


Figure 2-3: Drilling casing (Schlumberger 2015)

The safety demands, environmental and financial consequences of a wellbore collision occurring as a result of failure in casing can be catastrophic and very costly which makes casing schemes one of the most important sessions in any drilling activity (Schlumberger 2015).

A cost analysis by Poedjono *et al.* (2007) using more than 100 offshore cost estimates to determine casing cost components as a percentage of the drilling budget showed that casing make up 25% to 35% of offshore drilling budgets. In addition to the high percentage ratio of casing schemes to the total drilling budget the authors also noted that at least 1 in every 4 drilling projects had a casing scheme failure (Poedjono *et al.* 2007). A cost model by itself cannot determine this but using knowledge and lessons learnt from reported cases can help in making realistic cost estimations in order to reduce the overruns of future projects. The need to have a better understanding of the cost impacts of different casing schemes have also been raised in the operation review report by Schlumberger (2015) which showed that the conventional casing method of stabbing accounted for most of the inherent risks in casing. It therefore seems that failure to make financial provisions for process failures in casing has a high probability to bring about delays and consequently cost increases above the budgeted amount. Hence to ensure rigour and robustness in cost estimations, provisions for both the actual cost of casing schemes and its cost of failure should be added.

2.3.3.3 Cement logging

Cementing in drilling is the process of mixing a slurry of cement, cement additives and water and pumping it down through casing to critical points in the annulus around the casing or in the open hole below the casing string (Schlumberger 2015). The principal functions of the cementing are to restrict fluid movement between the formations and to bond and support the casing (Halliburton 2009, and Schlumberger 2015). Cementing is therefore a critical component of well architecture as it provides mechanical support for casing by preventing fluid corrosion and most importantly isolating permeable zones at different pressure regimes to prevent hydraulic communication (Schlumberger 2015). Industrial review findings by Schlumberger (2015) and Halliburton (2009) disclosed that the integrity of cement logs to a larger extent determine the quality and speed of the drilling operation. Thus the quality of cement fill-up between the casing and the reservoir rock ensures smooth drilling operations (Halliburton 2009, and Schlumberger 2015). On the other hand, poor cement bond and poor fill-up of cement may allow unwanted fluids into the well which can damage casing and obstruct the drilling process thereby causing delays and increases drilling cost (Halliburton 2009). Though cement logging normally takes 10 to 50 hours to complete, excessive pressure and temperature from the well can double the time resulting in extra cost burdens to the operator (Halliburton 2009).

Challenging environments such as the offshore deep-water sector specifically present extra technical and logistical constraints to the cementing operations because the risks involved are such that no single method of cementing may be adequate to handle them. Schlumberger, a major service provider in this industry, proposed a combination of methods in these circumstances (Schlumberger 2015). It was suggested that slurries should be applied to isolate the formation of rocks since it can help to develop compressive strength faster than conventional cement systems. Again, lightweight cement logging is ideal for zonal isolation and the life of the well (Schlumberger 2015). Past performance reviews from Schlumberger and Halliburton on the failure to align cement jobs to wellbore temperatures showed a negative effect on slurry thickening time, rheology, stability (settling), set time and fluid loss. Generally, all these factors are known during drilling but finding the desired balance of cement properties for the job always remains the challenge (Schlumberger 2015). On average cementing is 25% of the total cost of well drilled which indicates that it has the potential to escalate costs should anything go wrong with it. This discussion indicates that a wide range of skills and experiences are needed in making the cost estimates for drilling projects which is often beyond the expertise of some cost engineers or estimators.

2.3.4 Delays

Delays in the context of the offshore drilling industry is defined as any occurrence that can slow down drilling activity without stopping it entirely. Delays ultimately lead to time and cost overruns beyond the date the concerned parties have agreed upon for the delivery of the project. Enshassi *et al.* (2009) explained that delay is not only expensive, but also a threat to project success in terms of time and cost and has huge cost effects on contracts and reputation. Offshore drilling operations demand many logistical support activities ranging from project procurement, expediting and integrated supply chain solutions offshore drilling, freight forwarding services, marine vessel chartering and offshore logistic support, aviation scheduling and support, material movement services, container hire, waste management solutions, dangerous goods storage, catering, health services, decision making and many other essential services that have a direct effects on drilling activity (Poiate *et al* 2006, Yang and Wei 2010) . Delays from the supply of these services equally means drilling operations would be affected and hence increase in the cost of drilling. Drilling time delays and cost overruns are very common in all the oil and gas producing regions and countries but particularly frequent in the Middle Eastern, Africa, and South American producing regions (Yang and Wei 2010). Poiate *et al.* (2006) analysed the impact of logistics delays on cost overruns in the Middle Eastern and African oil and gas industry and claimed that bureaucracy in procurement approval, incompetence of contractors and subcontractors to deliver needed logistics on time, inadequate tendering practices, and late internal approval processes were the major contributors to the delays in oil and gas project construction.

Similar to the findings from the Middle East and Africa oil and gas industry, Yang and Wei (2010) conducted cross-sectional studies using historical drilling costs of projects on some Asian and Middle East countries to analyse the extent to which delays in logistics can contribute to project time and cost overruns and found that more than 60% of drilling cost overruns are as a result of delays emanating from contractors and subcontractors' inability to supply required logistics on time. The researcher argues that this type of cost can be handled through a change of suppliers and making contractors liable for the cost of delays resulting from their negligence. Again, the research suggests consideration of delays as part of cost components in offshore drilling is crucial especially because of its consistent occurrence. Han *et al.* (2009) in their study on causes of overruns on mega projects found that highways and railways projects experienced a combined overrun of $18.4billion between 1998 and 2004 as a result of delays in logistics. This demonstrates the financial burden delays bring on projects if adequate measures are not taken to mitigate or control the delays during cost estimation for projects. Studies by Elinwa & Joshua (2001) on the cost of delays to public projects budgets in Nigeria, Sambasivan & Soon (2007) in Malaysia, Marzouk *et al.* (2008) and Adnan *et al.* (2009) on Jordan and Iran respectively all point to the fact that delays in logistics is one of the cost drivers to cost overrun that demand urgent consideration in building cost models. Using past data and experiential knowledge to develop a probability is one of the robust ways to represent delays (Idrus *et al.* 2011, Garcia-Crespo *et al.* 2011) when developing cost models for the offshore drilling industry.

An additional argument for logistics delay as a contributory factor to cost overruns in the offshore industry can be exemplified in the abandonment of drilling projects in some marginal offshore fields in Delta State of Nigeria due to lack of logistical support (Omoregie & Radford 2006). Enshassi *et al.* (2009), argued that any form of delay in logistics to the owner is a loss of revenue and threat to other potential project investment; to the contractor is a higher overhead cost because of longer work period, increase material costs through inflation, and higher labour costs; and to the government loss of taxes and royalties (Omoregie & Radford 2006, Rahman *et al.* 2013, and Enshassi *et al.* 2009).

2.3.5 Drilling administration and management as cost overrun factors

There are many internal and external factors that affect offshore drilling operation cost but seem difficult to estimate due to lack of comprehensive data. These factors which are key drivers of cost overruns include drilling planning and management, legal issues, economic factors, politics and environmental issues (Kaiser 2009, Azhar *et al.* 2008, Powell & Scyoc 2011, and Trading Economics 2015).

2.3.5.1 Poor site planning and management

Generally, every well site globally is typically characterised by three main descriptions. These are the geographic location as determined by its longitude and latitude, distance of the well to the nearest onshore service station and the water distance (Kaiser 2009). Geographic location plays an important role in the determination of the final cost of a drilling activity since there are always some unique risks that may require specialised skills and servicing. Azhar *et al.* (2008) investigated how poor site management can trigger environmental contamination and specifically assessed how the drilling of more than 100 wells caused contaminations to the environment that resulted in cost overruns. The findings indicated that due diligence be done to ascertain the location where the wells will be drilled in order to obtain region, country and territory government regulations and permits (Azhar *et al.* 2008). Azhar *et al.* (2008), and Powell & Scyoc (2011) argued that identification and evaluation of potential well risk is key to ensuring well integrity during drilling operations which starts with accurate site report. The authors claimed a significant number of offshore drilling operations have failed to meet the expected cost range because of poor risk screening during site description. A review of 10,000 operating wells in North America revealed that for safety, environmental and economic reasons it is necessary to identify and evaluate critical risks associated with any drilling activity (Powell and Scyoc 2011). No matter how robust and rigorous a cost estimation model might appear if the well site data used to develop it is inaccurate the model results would consequently lack validity. A study by Angelo and Reina (2002) on the geology, technology and site characterisation of the Alberta oil fields in Canada suggested that failure to spot areas with the greatest risk early enough for detailed analysis and efficient resource allocation has 40% chance of leading the entire drilling operation to cost overrun.

Furthermore, several research findings have revealed that most of the causes of time and cost overruns in mega projects relate to the human and management problems (Chan 1998, Lo *et al.* 2006, and Acharya *et al.* 2006). These findings reflect the common challenge of human error in project execution across the globe. Ogunlana *et al.* (1996) posited that poor management is among the top 3 causes of cost overrun causes in all construction projects in Thailand. Similarly, poor management was rated to contribute between 20 to 50% of cost overrun in all major projects (Kaming *et al.* 1997) in Indonesia. Similar findings were found by Chan & Kumaraswamy (1996), Kumaraswamy & Chan (1998) and Sambasivan & Soon (2007) in Malaysia, Lo *et al.* (2006) in Hong Kong, and Acharya *et al.* (2006) on Korean outlook. These reports indicate that poor management is a critical problem in many industries and has a direct effect on costs hence the need to properly factor them into cost generation of projects. Reported cases of poor management in drilling is not peculiar to Africa and the Middle East but is a global phenomenon that plagues the entire industry. A range of studies across many countries has unanimously rated poor management as key contributor to project cost overrun, thereby highlighting the need to minimize cost overrun through the adoption of an efficient management style (Mansfield *et al.* 1994, Odeh & Battaineh 2002, Frimpong *et al.* 2003, Koushki *et al.* 2005, Aibinu & Odeyinka 2006, Assaf & Al-Hejji 2006, Faridi & ElSayegh 2006, and Sweis *et al.* 2007).

Recounting the many accidents in the oil and gas industry due to management failures such as the Piper Alpha disaster in 1988 in the North Sea UK which claimed the lives of 167 men and resulted in US$3.4 costs and the Deepwater Horizon oil spill in the Gulf of Mexico being the largest offshore oil spill in US, accentuate the need to review the impact of poor management, not only because of financial losses it engenders but also for its part in ensuring safety of lives and properties (Miller 1991, and Gerald 1998).

2.3.5.2 Legal

The current type of contract signed for drilling operations in the offshore oil and gas industry is detailed and comprehensive as a result of past precedence of unassigned liabilities to parties in contracts that has led to several court suits (British Petroleum 2010). It is because violations of laws during drilling and any negligence resulting in accidents, loss of lives or damages to the environment ultimately have a cost element which often contribute to drilling cost overrun (Kaiser 2009). Since the offshore deepwater drilling sector engages contractors for the most part of their operation, it is important that the financial liability in drilling operations for the operator is understood and included in the project cost estimation (Miller 1991, BP 2010, and US National Commission 2010). Oil operators play a significant role in determining the contract type since they tend to suffer more financially in the event of legal claims. The BP oil spill at Macondo in 2010 serves as reference point for learning in this regard as an amount of more than $20billion USD has been paid for these purpose (BP 2010, Ernest and Young 2015). Therefore, operators and contractors agree through contracts on where the well is to be drilled, how it should be drilled, and the specification of the drilling (i.e. whether to drill only a well or multiple of wells). Because of the risky nature of offshore drilling and repeated cases of contract breaches it is proactive for cost estimators to anticipate this and act decisively (Osmundsen *et al.* 2008).

Moreover, whether the contract type signed is day rate or turnkey (paid after project is completed), it is necessary that operators are aware of the impact each of these has on time and cost of drilling projects (Osmundsen *et al.* 2008). The researcher proposes the modelling of contract types to ascertain their effects on the time and cost of offshore drilling projects is more rigorous to show whether or not a certain type of contract has any contribution at all to cost overrun. Contracts in the offshore deep-water drilling industry and many other construction companies have a great impact not only on their respective companies but on the economy of the host country (Statistic Canada 1997). Cost overruns as a result of contracts have grown for 20 years considerably in many parts of the world and particularly in the US (Construction

Industry Institute 1986). These cost overruns can be attributed mainly to the inappropriate risk allocation in contracts which can hinder other potential investments and result in cost escalation in the process (CII 1986, ACE &AGC 1991, Enger *et al.* 1997, Hartman 2000, and Zaghloul & Hartman 2003). Drawing on previous cost overrun experiences and incidences in the oil and gas industry, there is ample evidence suggesting that failure to understand the legal framework governing the offshore deep-water drilling industry and proactively allocating the needed cost cover in the project cost estimate will eventually result in cost overrun. For example, the Pilot commercial development (PCD) of marine oilfield Kashagan (Kazakhstan) in 2005-2009 saw costs double to $14.1billion from an initial cost estimate of $7billion; Bonga Oil field in Nigeria (2001-2005) witnessed a similar challenge resulting in an overrun of $4billion from a budget of $2.7billion (IEA 2010, Mining Weekly 2012, Bloomberg 2012).

Also, failure to include legal liability which shields parties from liabilities arising from project delays, accidents and mistakes can cause overrun when disclaimer clauses (the medium through which this is achieved) are not added to the contract (Hartman 2000). These clauses allow one party to transfer risk to the other through contractual terms to prevent paying for unbudgeted costs. Studies have shown that failure to make financial provisions for legal costs in project cost estimation is one of the weaknesses that require active redress (Khan 1998, and Jergeas & Hartman 1996). It is therefore important to know risk owners in any project between parties to ensure accurate cost estimations (Zaghloul & Hartman 2003). Industrial practice has proved that the use of disclaimer clauses in contract terms contribute significantly to increase in cost overrun in projects, justifying the importance of having broader knowledge on the part of cost estimators as part of the measures to reduce cost overrun problem (Statistic Canada 1997, CII 1988, Hartman 1993, Khan 1998, and Jergeas & Hartman 1996).

Finally, evidence from past overrun cases has further shown the relevance of incorporating them in cost estimates. Edwin & Ann (2005) argued that whether it is a lump sum contract where payments are made on agreed milestones or bills of quantities which split work into components and materials and labour cost are settled, it rarely covers issues about risk and uncertainties. This ends up escalating costs resulting into conflicts between operators and contractors in the industry, hence the need to find ways to add this when formulating a cost model. Again, the legal costs paid in excess of $40billion by BP as a result of the Macondo oil field spill offers vital lessons on the need for proper risk appropriation in contracts (BP 2010). Likewise, an evaluation done on three oil companies in China on contract management covering policy risk, financial risk, operational risk, efficiency risk and market risk shockingly revealed that companies lose on average $10million due to lack of risk appropriation in contracts (Wang & Sun 2012). In a study focussed on accomplished drilling projects in Hong Kong Daniel *et al*. (2011), noted that high-risk factors should be managed in a proactive manner during contract development as they have the ability to escalate budget costs of both contractors and operators. These findings therefore demonstrate that to develop an improved cost estimation model, impacts of legal issues and how they can be quantified into cost estimation models must be addressed.

2.3.5.3 Economic

Operations in the offshore drilling sector are affected by economic and financial factors most especially in the Sub-Sahara Africa due to the volatile nature of these economies (Trading Economics 2015). Inflation, which is the persistent rise in prices of goods and services, and currency depreciation rates, which is the performance of a country’s currency against the US dollar (widely used currency for all trading and contracts), are volatile in Ghana, Nigeria and Angola which drive cost overrun

(Trading Economics 2015). The offshore deepwater drilling market is such that prices are charged according to the market rates of the host country which makes the problem of inflation and weak currency a problem (Osmundsen *et al.* 2008 & 2009). Hence, the inability of governments to accurately forecast inflation figures affects the cost of drilling in these three countries. Reviewed economics reports showed that the predicted average inflation of 8.5% and the actual inflation average of approximately 20% of Nigeria, Ghana and Angola between 2005 and 2015 show yield 50% increase in cost as a result of inflation overrun (Trading Economics 2015). Evidence from past drilling cost data from these three Sub-Sahara countries show consistent overrun of inflation figures which subsequently contributed to cost overrun of projects (Tullow 2014, Shell 2014, and ExxonMobil 2014). Although it is in the remit of economic management teams and various central banks to determine inflation figures, it is equally important for oil operators to get those figures right as their operations are directly affected by this indicator.

Moreover, the World Bank, the International Monetary Fund (IMF) and several other financial institutions have raised deep concerns about the inability of central banks in Africa to achieve their set inflation and exchange rate targets (The World Bank 2015). As many industries rely on the forecasted figures for these economic indicators for their estimations companies end up being disappointed as a result of the overreliance of such data (The World Bank 2015). Comparative analysis of the indicators of the Sub-Sahara countries under consideration from 2005-2015 with countries such as United Kingdom, United States and Norway where inflation average for that same period is below 3% show the extent to which high inflation impacts this region (The World Bank 2015). Similarly, the currency performances of the Cedi (Ghana), Naira (Nigeria) and the Angolan Kwanza compared to the US dollar have been abysmal under the years been reviewed (Trading Economics 2015). The average exchange rate of Ghana Cedi's to the US dollar from 2005 to 2015 is 3.5GH: 1$US. Equally, the Nigeria Naira averaged 127.56: 1USD while Angolan Kwanza was 57.73: $1USD (Trading Economics 2015). Analysis of the average currency performances of these three countries against the US dollar showed that drilling cost is approximately 60% higher in Ghana, a little over 65% and more than 75% in Nigeria and Angola respectively when compared to a country like the United States. Therefore, to reduce cost overruns in offshore deepwater drilling projects, it is vital to analyse and include the true cost of inflation and currency depreciation rates in cost estimation models.

2.3.5.4 Politics

Bribes and corruption are deep-rooted in the politics of most African countries and are similarly rampant in most public institutions (Transparency International 2015). Report by Transparency International, a global organization that evaluates and ranks countries based on transparency in governance, bribes and corruption perceptions showed that the lack of transparency breeds bribery and corruption and since the majority of governments in Africa do not subscribe to the idea of transparent governance the problems that come with it remain prevalent in this continent (Aibinu & Odeyinka 2006, and Transparency International 2015). Payment of bribes is a *de facto* cost factor in every project in the Sub-Sahara Africa and some parts of Africa in general (Aibinu & Odeyinka 2006, and Transparency International 2015). In fact, there is hardly any project that lacks allocation of bribes to top officials or power brokers in this part of the world (Aibinu & Odeyinka 2006, and Transparency International 2015). As bad as it may seem, it has become culturally acceptable to pay bribes without which genuine businesses or contractors are denied contracts for the sake of it. In context to the scope of this study, there have been reported cases of political influence, payment of bribes and some corrupt activities in the awarding of drilling contracts in Ghana, Nigeria and Angola (Transparency International 2015).

Report by Transparency International in its global corruption index publication rated Angola 161/175 and an average transparency index of 19 in the last decade making it one of the highly corrupt countries (Transparency International 2015). Likewise, Nigeria recorded 136/175 with an average transparency index of 25 in the last decade representing a high corrupt state (Transparency International 2015). Ghana was better compared with the other two countries with an average transparency index of 46 in the last decade making it 61/175 in terms of the global corruption ranking (Transparency International 2015). Though these payments are directly non-productive to the projects, cost estimators need to be aware and somehow reasonably predict how much it might cost for a project (Aibinu & Odeyinka 2006). As difficult as it may be to know the amount to apportion to each project because of the discreet nature in which such payments are made, it is absolutely prudent for cost estimators to make provisions for them. Evidence from 800 offshore drilling costs analysed in Nigeria from 1996 to 2009 revealed that operators pay not less than 10% of the entire cost of a drilling project as bribes (Aibinu & Odeyinka 2010). Similar deductions can be made in the other Sub-Sahara countries which emphasis the need to avoid treating bribes and corruption as trivial issues in cost estimation.

2.3.5.5 Environment

The other external factor that contributes to time and cost overrun of offshore deepwater drilling projects is the effects of environmental activities. Unfavourable weather conditions such as strong winds, excessive heat and high wave currents are common in offshore deepwater drilling operations along the Atlantic Ocean where the three Sub-Sahara countries are situated. Almost every offshore deepwater drilling operation faces either strong winds or high wave currents, and even worse is the Artic regions where operators have to contend with the icy conditions in addition to the other two mentioned (Kaiser 2009). The Atlantic Ocean in the of Sub-Sahara Africa is not an exception to these problems as reports from Ghana, Nigeria and Angola confirm the need for operators to endure high wave currents especially at night and when it rains due to the occurrence of harsh strong winds in those conditions (Kaiser 2009, and Kaiser & Snyder 2013). As much as these factors are known, it still remains quite difficult to determine the cost of poor weather on drilling operations without having adequate knowledge and past experiences of such occurrence on past projects. The normal practice has been the use of past precedence to forecast the likely outcome of these factors on costs. As there is no standardize approach to determine this, companies make their own predictions based on the company's perception and their risk tolerance level (Halliburton 2009, BP 2010, and Kaiser & Snyder 2013). It is against this backdrop that the current study seeks to develop a formal elicitation process for eliciting responses from experts to facilitate better results for cost estimation models.

2.4 Uncertainties

There are other variables that contribute to cost overrun that make it difficult to envisage how, when and why they happen. Nonetheless, these uncertain or unknown factors still have to be accounted for when estimating the cost of projects. These uncertainties which in the context of this study are termed "the unknown unknowns" share the same meaning in practice in the oil and gas industry (Yoe 2000). The standard practice in accounting for the unknown unknowns in the oil and gas industry and the offshore sector in particular is by adding a minimum of 10% of the total cost of the project to be the budgeted amount (Hall & Delille 2011). There are however some variations in the allowance reserved for the unknown unknowns from company to company as the percentage allotted are sometimes largely influenced by the experiences learnt from past projects as well as the perception of the operators (Hall & Delille 2011). Sawczuk (1996) investigated how accurate the 10% allowance of total cost of project earmarked to reflect the cost effects of the unknown unknown variables was, and concluded that, since the same allowance is expected to make up for any variation in the other cost variables either than the uncertainties, the 10% is deemed inadequate. Yoe (2000) agreed with Sawczuk on the need to strive for precision in cost estimations on variables that have available data so that any percentage allocated for uncertainties can serve that purpose. However, since uncertainty can originate from known or predictable variables, it becomes difficult to allocate a percentage of a project budget for the sole purpose of managing uncertainties without regards for the variables or factors that generate these events.

Therefore, this study acknowledges the need to comprehensively improve the accuracy of the known unknown factors while maintaining the 10% allowance for any unforeseen events arising from the cost factors. Hall & Delille (2011) argued that the relevance and purpose of creating a project allowance is aimed at reducing cost overrun and so if pragmatic measures are not taken to improve the estimations of the cost drivers, that purpose is defeated. Because cost overruns occur as a result of failures of cost estimators to either explain or enlarge the error levels, in the formulation of a cost model to address these challenges, emphasis should be on eliminating or drastically reducing the overruns resulting from the known variables. Again, the position of Hall & Delille (2011) supports the research goal of improving the accuracy of the predictions of the known unknowns using expert judgment elicitation process based on Bayes Theorem.

Figure 2-4 below summarises the major causes of cost overrun in the offshore drilling industry into a flow chart showing the critical factors (from the known unknowns) and the basic cost elements (known knowns) based on the evidence discussed above. It also portrays what the model to be developed in the course of the study should capture in order to reduce cost overrun. As discussed in this section, the effects or cost impact of the critical factors must adequately be assessed and added to the drilling cost elements before accurate cost estimates can be achieved.

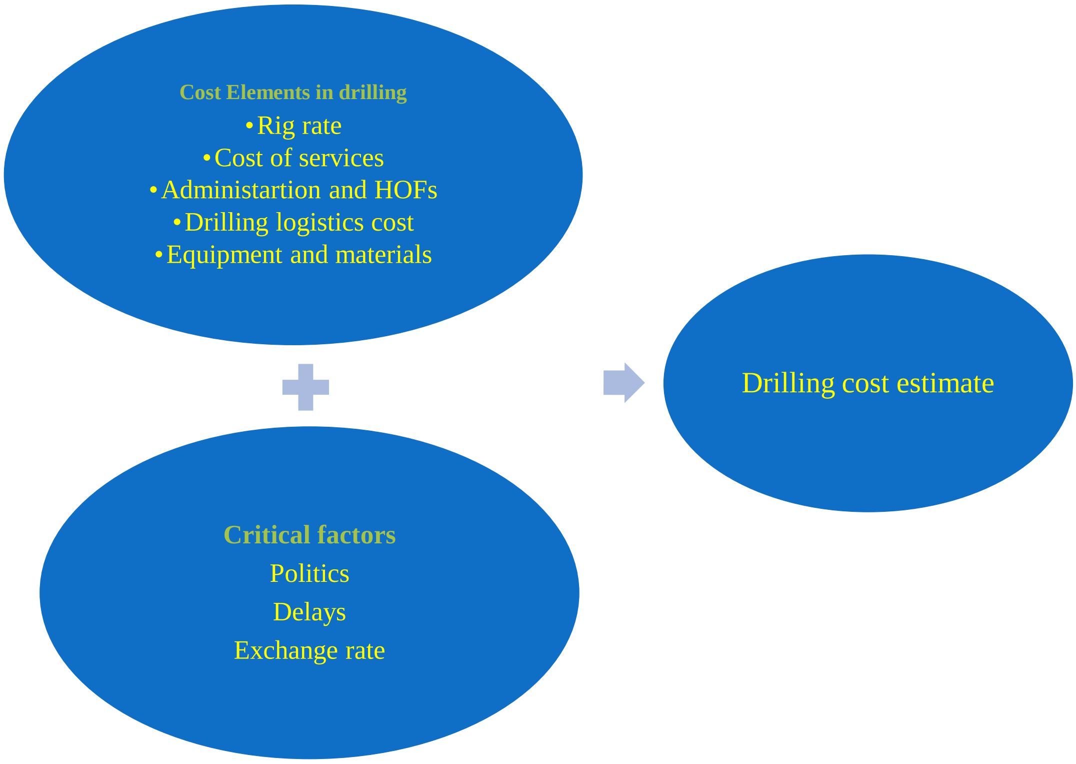


Figure 2-4: Summary of drilling cost elements and critical factors

Source (conceptual cost model was developed based on findings from Poiate *et al* 2006, Aibinu & Odeyinka 2006, Osmundsen *et al.* 2008 & 2009, Enshassi *et al.* 2009, Yang & Wei 2010, Idrus *et al.* 2011, Garcia-Crespo *et al.* 2011, Transparency International 2015, Trading Economics 2015, and The World Bank 2015)

2.5 Chapter summary

The chapter discussed the operational set up for offshore deepwater drilling and analysed the risk and complexities in the operations. To achieve a more improved cost estimation model compared to the current ones, it was found that understanding and adding the relevant data from human and organizational factors (HOFs) and technological risk, geological risk and operational risk into the model development is essential (Aven *et al.* 2006). In addition to this, a review of the cost overrun causes suggested that current models are insufficient in helping to solve cost overruns. Delays in logistics, decision making and project execution were argued to have 60% likelihood of cost overrun in Africa (Poiate *et al.* 2006), drilling services factors such as casing scheme and cementing were found to have the ability to increase costs by more than half their planned budget across the globe (Poedjono *et al.* 2007 and Schlumberger 2015) through the effects of political and poor local currency exchange rates against the US dollar. Analysis of the impact of equipment failure and material delays revealed that they have a potential probability of 26% of cost overrun and that factors such as legal, economic, politics and environment have more than 65% chance of causing cost overrun especially in the Sub-Sahara Africa (Enshassi 2009, Yang & Wei 2010, and Rahman *et al.* 2013). Notwithstanding, these findings from the literature, Liu & Samull (2008) and Kaiser (2009) proved that the cost of rig is the only “known known” factor in cost estimation while the others can be classified into “known unknown (cost drivers)” and the “unknown unknowns (uncertainty)” in accordance to the offshore drilling industrial practice (Yoe 2000).

The literature review also shows that the ability of cost estimation model to accurately estimate the known unknowns (drilling services, logistics, equipment and materials and administration and management) can reduce the industry cost overrun from 40%

to less than 20% of the total cost of offshore drilling projects. Understanding this informed the direction of this research which aimed to investigate the extent to which a combination of Bayesian technique and a cost model can deliver an improved cost model compared to the current cost models. The next chapter discusses cost estimation models techniques and their requirements with the aim to identify the right cost model to be integrated with the Bayesian technique

Chapter Three

MODELLING REQUIREMENTS FOR COST MODELS

3.1 Introduction of the chapter

The chapter gives a brief introduction to models and modelling in section 3.1.1. Section 3.2 discusses modelling, types of models and the requirements of a cost model for the oil and gas industry. The chapter ends by emphasizing the key points discussed in the summary section 3.3.

3.1.1 Brief introduction to models and modelling

The general definition for a model is a "human construct that helps to better understand real world systems" (Rumbaugh *et al.* 1991). In other words, it is the representation of the real world phenomenon into an equation, shape, size or style etc. that can mimic to a larger extent the behaviour or system performance. The process of representing the real-world object or phenomenon as a set of mathematical equations is therefore known as modelling (Rumbaugh *et al.* 1991, and Ford 2009). In general, all models have an information input, an information processor, and an output of expected results (Ford 2009). Because models only approximate natural phenomena, they are inherently inexact suggesting perfect models are hard to come by (Rumbaugh *et al.* 1991 and Ford 2009). It is important therefore that these features are specified at all times in any modelling process to help in the understanding of the model and more importantly its usage (Ford 2009). In addition to the key components for modelling, what the model does must be clearly defined before it is developed so as to avoid ambiguity and to ensure a fair assessment of the model performance. This is because a model can also be validated and verified using the proposed model definition and results (Ford 2009). Rumbaugh *et al.* (1991) argued that understanding what the model does and what it does not helps clarify the purpose for model development which is as important as its definition.

Modelling entails adhering to certain fundamental principles at all times (Rumbaugh *et al.* 1991, and Hollnagel & Bye 2000). Firstly, the choice of model to be developed should be influenced by the nature of the problem. Secondly, since every model has different levels of precision this could be a guide in the model selection process. Thirdly, the most effective models have been regarded as those that strive to connect to reality or mimic the real world (Hollnagel & Bye 2000). Moreover, since no single model is sufficient enough to solve every problem, "every nontrivial system is best approached through a small set of nearly independent models with multiple viewpoints" (Hollnagel & Bye 2000). These principles suggest that choosing the right model has a high likelihood to illuminate development problems by offering insights that simply could otherwise not be gained whereas wrong model on the other hand has the potential to mislead and direct focus on irrelevant issues.

A formulated model that follows the discussed principles has a range of benefits if properly designed: it helps to visualize a system as it is or as it is intended to be; provides the opportunity to specify the structure or behaviour of a system; can be used as a template that guides in constructing a system; and can be used to document the decisions made (Schwartz & Kent 1989, and Weinreb *et al.* 2005). Usually, models are the only means to extrapolate large spatial scales or predict the future, and because of their importance, it is essential to assess model accuracy by calibrating and validating them (models) (Weinreb *et al.* 2005). Again, to help quantify the uncertainty of the model output, sensitivity tests are run to determine the magnitude of change of the model output to possible changes in model input or parameters. The limitations of models are identified and improved on during calibration, validation and sensitivity analysis which make these three steps vital in the formulation of any model.

3.1.1.1 Types of models

Models are mainly designed to solve problems and in the words of Adhitya *et al.* (2007) it is fitting to develop models based on the needs of a system/process and not to adapt systems to the demands of a model. Models can be categorised into four main types namely; (1) conceptual models, (2) interactive models, (3) mathematical and statistical models, (4) and visualization models (Siau 2004). Conceptual models are qualitative document that are used for the purpose of understanding a problem and communicating the connections in real world systems and processes (Siau 2004). Often (1) conceptual models are developed into more complex models (Siau 2004). Moody (2005) evaluated the quality of current state and future directions of conceptual models based on theoretical and practical issues and concluded that conceptual models lacked quality standards and definition in practice. The model developed in this thesis built upon the recommendation of Moody (2005) by first defining its purpose and the problem it intends to address. Secondly, (2) interactive models are physical models of systems that can be easily observed and manipulated and are usually used for demonstration exercises (Avison & Fitzgerald 2003). They bridge the gap between conceptual models and models of more complex real world systems and are best utilised for experimental purposes (Avison & Fitzgerald 2003, and Siau 2004). Thirdly, (3) visualization models just like the interactive models are used to show how a system works. Images, animals, maps and other similar tools can be used for this purposes (Avison & Fitzgerald 2003, Siau 2004). Avison & Fitzgerald (2003) argued that these three models lack rigor and robustness and are therefore not recommended for use in the domain that require making critical decisions.

More specifically, Avison & Fitzgerald (2003) has critiqued conceptual, interactive and visualization models, suggesting they are less capable of addressing the problems of cost overrun in the offshore drilling sector. This is because they lack the ability to identify and analyse relationships that exist between cost variables and drilling activities or to utilize relevant equations and statistical parameters in model development. The fourth model type, (4) mathematical and statistical models which involve the use of equations, statistical parameters such as mean, mode, variance or regression coefficients does not suffer from the limitations of the first three (Colmer 2005, and Collopy & Curran 2005). Hence the reason for its adoption in the current research. The analytical abilities of mathematical and statistical models make them suitable to be used for making predictions and forecasts. Moreover, there is evidence of complex problems having been solved by the use of these models (Kitchenham 1992, Siau 2004, Colmer 2005, Collopy & Curran 2005, Theodorsen 2010, Theodorsen 2011, and Hall & Delille 2011) hence the choice of statistical model is best placed to offer the needed rigor, robustness and analysis in developing an improved cost estimation model. To examine and review the appropriate models minimising cost overrun, the next section discusses the requirements for cost estimation models in the upstream drilling industry.

3.2 Cost estimation model requirements

There are different kinds of cost estimation models and formulation process. A common type of model developed to estimate the cost of project or product is usually expressed in mathematical equations (Marbán *et al.* 2008, and Sharma *et al.* 2011). There are shared requirements in the constructing of cost models irrespective of the project, business or industry the model is built for (Sharma *et al.* 2011). Every cost model functions through the input of parameters that describe the characteristics of the project in question, and possibly the physical resource requirements. Different inputs such as market data, prices of goods and services, machine performance, and many others can be used in building these models depending on the type needed for the project or product in question (Garcia de Soto *et al.* 2014). The model then provides a cost outcome using the input resources requirements in cost and time. It must be emphasised that there is no best approach or method to cost estimation but appropriate model choice can be made depending on the nature of the input data, estimate parameters and the desired output. Again, there has been a major change in the trend of usage as majority of models were constructed manually in the past but recently the development of cost models is almost universally computerised in every business (Garcia de Soto *et al.* 2014). The main use of cost models is typically necessary to obtain approval to proceed with a project, and are factored into business plans, budgets, and other financial planning and tracking mechanisms among many others.

Understanding of time and cost of projects therefore form the basis upon which important investment and operational decisions are made in the offshore deep-water drilling industry (Marbán *et al.* 2008, and Sharma *et al.* 2011). Knowledge of the time and cost of projects are derived using estimations models (Sharma *et al.* 2011). Generally, every model has a set standard and requirement to comply with, of which cost estimation models are no exception. Hence just like any cost estimation model, there are requirements and standards for cost estimation models in the offshore deep water drilling industry (Garcia de Soto *et al.* 2014). This next section discusses the six core requirements cost estimations should have and the criteria they should meet in the offshore deep-water drilling industry. These requirements are (1) definition and purpose, (2) theoretical underpinning and assumption, (3) input data, (4) risk capture and robustness, and (5) suitability and applicability of the model.

3.2.1 Model definition and purpose requirement

The first demand on any offshore deep-water drilling cost estimation model and every good model in general is to unambiguously define and state the scope and purpose of the model (Akaike 1973 and Theodorsen 2010 & 2011). This helps to trace the origin and identify the problem the model hopes to solve (Akaike 1973, Theodorsen 2010, & 2011). Hall & Delille (2011) argued that a model without a definition and specific purpose is of no use no matter how rigorous it may appear. Since most models are developed to solve peculiar problems, it is therefore important that every model passes this basic test (Theodorsen 2011). Evidence from a review on time series analysis hypothesis on offshore deep-water projects showed that poor definition always results in poorer model formulation and performance (Lehntan 1959, Theodorsen 2010 & 2011). This argument cannot be limited to any specific industry or project but is valid for every operation that uses models. In reviewing some statistical estimation models for engineering projects, inadequate definition was found to be a relevant criterion statistical models must achieve, which supports the need to uphold this requirement in model development (Akaike 1974, Theodorsen 2010 & 2011).

Jebaraj & Iniyan (2006) reviewed more than one hundred cost models and concluded that every model uncovers the existence of a problem which is supposed to be found in the definition. Clearly identifying and defining a model seems important since each project has its own uniqueness and risk (Chapman *et al.* 1985). This therefore suggests that objective evaluation of model performance and identification of errors or gaps that require attention cannot be done without defining the problem. Using data from British Petroleum offshore projects in the North West Europe region, it was recommended that all models in the oil and gas industry define the scope and area of coverage since the industry is very complex and huge (Theodorsen 2010 & 2011).

Again, since most models in the oil and gas industry are developed with the intention of solving a problem, definition of models would ultimately help oil operators make correct model selection to address specific problems and also inform researchers on existing gaps in research.

3.2.2 Theoretical underpinning and Assumption

Again, another way to measure the usefulness of a cost estimation model is through the underpinning assumption and theory upon which the model was built (Kitchenham 1992). Every sound cost estimation model is a product of well thought thorough assumptions (Boehm 1981, Kitchenham 1992, Theodorsen 2011, and Hall & Delille 2011). It was suggested that every cost estimation model assumption should take into consideration the relationship between the variables required for the model (Boehm 1981 and Kitchenham 1992). This enhances the theoretical validity of the model as the variables inform the choice of the assumption (Kitchenham 1992, Theodorsen 2011, and Hall & Delille 2011). It can be added therefore that model assumptions should be linked to the theory that explains the research problem.

Kitchenham (1992) debated that assumptions vary from model to model depending on definition and purpose, and that the choice of variables or factors opted for a model should support model assumptions. While there is evidence to support Kitchenham’s claim that cost variables can influence assumptions, the current study supports Kocaguneli *et al*. (2012) who outlined the elements any cost estimation model assumption should have. The first was a selection of a predictive system which forms the foundation for the estimation, second is to identify the essential assumptions of that predictive system chosen and third is to recognize situations that can violate the essential assumption made for the predictive model. Harrell *et al.* (1996) argued that the type of model determines the kind of assumptions to be made. Thus sometimes assumptions made during regression modelling may not be applicable in optimization, statistical or probabilistic modelling. The researcher will adopt the suggested requirements of a good assumption by Kocaguneli *et al* (2012) alongside the core assumptions for the model to be developed (Harrell *et al.* 1996). In the case of regression models, Harrell *et al.* (1996) suggested three basic assumptions. Firstly, the linearity rule which assumes that "for a certain scale of Y, each predictor variable X is linearly related to Y" (Harrell *et al*. 1988). Secondly, is the assumption of additivity of effects of predictors. Thus interaction between variables can be tested by adding subset/parts that explains each of the variables. Finally, is the distributional assumption which deals with the proper specification of the X-structure of the model (Durrleman & Simon 1989, and Sleeper & Harrington 1990). When predictor variables for the model are confirmed, it makes it easier for distributional assumptions to be made and verified.

3.2.3 Input data requirement

The quality of model results is directly dependant on the quality of data input used. Chou (2011) explained the differences that exist between cost element and cost drivers. While cost elements are the basic inputs of cost models which answers the "what is", it is important for the model to capture the cost drivers which are the "what if's". Chaudry *et al.* (2013) argued that the quality and accuracy of a cost model is dependent on the trade-offs uncovered by the cost drivers. This also agrees with Garcia de Soto *et al.* (2014) point that a cost model is as good as the data used. Therefore, in order to improve this data a number of scholars (Zhang *et al.* 1996, Collopy & Curran 2005, and Idrus *et al.* 2011) identified the need to triangulate around the data input to improve accuracy and confidence. Thus the use of multiple data points helps to verify and check the integrity of the data used in modelling. To ensure the quality of data, there are four core dimensions to consider which are completeness, uniqueness, validity, and accuracy/consistency (Batini *et al.* 2009) and this implies that

- ✓ The data being used for the modelling must be checked against the potential of "100%" completeness of the proportion of data stored.
- ✓ The uniqueness of the data must be verified such that no item is recorded more than once while the timelines of the data should represent the reality from the required point in time.
- ✓ The validity of the data must conform to the syntax of its definition and the data should have adequate accuracy that correctly describes the "real world" object.
- ✓ All the data must be consistent with the data definition and should be devoid of any differences (Batini *et al.* 2009).

Input data for offshore drilling cost estimating models and specifically mathematical and statistical model type are quantitative (Bryman 2007). Quantitative data input in cost models are the cost drivers whose primary data can be collected in the form of a number such as mass, length, weight and cost of an item whereas qualitative data on the other hand are the drivers whose data are mainly subjective text based data that contains concepts and ideas but are required to be converted into a numeric form (Dalal *et al.* 2011). Since the offshore deepwater drilling industry substantially rely on experience and subjective judgements in its operations, it is critical to utilize the capabilities, experiences and judgements of experts in the formulation of cost models to make it as robust as possible

3.2.4 Risk capture and robustness

Risk capture is defined as the ability to identify, assess and present risk in a numeric form in cost models (RRV 1994). According to Muller (1978), Maidl (1988) and other researchers such as Sarma & Adeli (1998), and Salazar (2010), the offshore deep-water drilling process requires structured way of capturing risk into models due to the many activities that are involved in drilling project. Maidl (1988), and Sarma & Adeli (1998) recognised that capturing risk in oil projects is inherently difficult primarily because of lack of information but nonetheless recommended the need to find alternative ways to address that challenge as they are crucial to ensuring the accuracy of cost model estimates. A study conducted by Mohammad (2012) on railway and highway cost estimation models revealed that using expert judgement and past data or risk in similar projects helps improve risk capture during modelling. Though there are clear differences between railway and highway projects and projects in the oil industry, they are similar in terms of the amount of repetitive work involved, the mix of skill, disciplines, and the expertise required and the high risks involved. In combination this make the findings from these projects applicable to the oil industry. Evidence from "Korea Train Express" a railway project investigated by Mansfield *et al.* (1994) and Han *et al*. (2009) showed that the ability to identify and adequately assign realistic cost values to project risks has the potential to reduce cost overrun by more than 50%. While this conclusion is plausible, it adds little to how risk can be captured and incorporated into models formulation process.

Elinwa & Joshua (2001) argued that since risk is a perception and varies among companies, risk capture could be done through numeric quantification of opinions and perceptions into models. Expert opinion is one of the ways to capture risk and minimise cost overrun. Findings by Sambasivan & Soon (2007) on Malaysian Public construction and Marzouk *et al.* (2008) on oil projects in Jordan showed evidence of the use of expert opinion to approximately capture 50% to 60% of project risk and improve project cost estimates. While the findings of Marzouk *et al.* have not be generally accepted as the standard measure of risk capture requirement for modelling, it can be suggested that its ability to capture half (50%) of a project risk should be a good starting point towards finding a unified measure for risk capture in modelling. However, Xiaotie & Miao (2011), and Dongkun & Xu (2012) argued that some cost estimation models are built on incomplete and inaccurate risk information and therefore recommended that 50% project risk capture should be the acceptable minimum limit as it has the potential to improve project cost estimates.

On the other hand, considering the risk and uncertainty in the offshore deep-water drilling operations, the need for a robust model seems essential. A model is said to be robust if "it still provides insight to a problem despite having its assumptions altered or violated" and offers insight to any changing pattern or problem in an activity/operation even when the assumptions or variables are altered (Hoogland and Boomsma 1998). Empirical evidence from the analysis of Monte Carlo cost models showed that there were contradictory conclusions about the predictive abilities of the models based on how robust each model is (Hoogland and Boomsma 1998). While models with high robustness gave consistent estimates despite changing variables and assumptions, the estimated values of the ones with low robustness changed drastically. A review by Wang *et al.* (2012) on the sensitivity of it on model performance concluded that the concept of robustness in modelling is very desirable as it forces model developers to always produce models with high estimation accuracy.

In recent years the persistent call for robustness in models is as a result of the increasing uncertainties and risks in mega projects such as oil and gas projects, construction and many others and the need for easy practical adaptation of models into the operational activities of industries (Collins-Thompson 2009, Dai *et al.* 2011, and Svore *et al.* 2011). It suggests therefore that models built with strong robustness can help minimise risk and improve estimation. Chalupnik *et al*. (2006) established that process robustness has the ability to bring expected results such as accurate project time and budget, and quality of products regardless of any unexpected adverse factors. Again, the ease to consider interdependences between variables and design process when a model is robust makes it a relevant factor for offshore drilling cost models. However, Chalupnik *et al*. (2006) warned about the costs associated with developing a solid and robust process or model stating that normally either a system or project needs to fail or extra resources are spent before improvements in robustness can be achieved in the real world. Hence it is vital to ensure that while robustness is being pursued, quality or performance of some parts of the project is not compromised (Elton & Roe 1998, Evans 2005, and Ford & Sterman 2003). Again, due to the complex nature of offshore drilling projects, robustness is required for almost every section of the project to ensure high performance and overall improvement (Chalupnik *et al*. 2006, and Harman 2007). It is therefore appropriate to use robustness as one of the measurement for assessing the fitness of an offshore deep-water drilling cost estimation model in the oil and gas industry because it stands to contribute significantly to the reduction of cost overrun in the industry.

3.2.5 Suitability and applicability

Another important requirement for a cost model is for it to be built to suit the operations or the process, industry or system it represent and be equally applicable to the day to day activities of that system. A model is considered suitable if it places importance on real world situations as well as having the ability to determine the question to be studied, data needed, criteria of analysis and the final model decision while applicability is the usefulness of the model for a particular task (Wildavsky 1966, and Liu *et al*. 2001). Orea & Kumbhakar (2004), and Woloson & Jones (2011) in their examination of models used in the oil and gas industry argued that since they are primarily adapted it is difficult to directly fit into the system and operation of the oil industry. They suggested the need to uphold this criterion in the formulation of cost models for the industry as real world problems are best solved when this criterion is upheld.

3.2.6 Validation and verification approach

Demonstrating the correctness of a developed model and reaffirming that the right model was built for the problem at hand (verification) are essential Pace (2004) (see section 7.3 in the model formulation chapter for more details). In support of other scholars (Liu *et al*. 2001, Orea & Kumbhakar 2004, and Woloson & Jones 2011) regarding the need to validate and verify model data input and results, the current study has dedicated section 7.3 in chapter 7 to address model validation and verification process. Considering the requirements that need to be met by the intended model (Bayes Theorem plus a cost model) other appropriate model techniques or methods that have potential to solve the research problem are reviewed in the next section.

3.3 Chapter Summary

The chapter discussed models and modelling and highlighted the different kinds of models available. Particular emphasis was laid on the prerequisite of the cost estimation model in the oil and gas industry. The six requirements which included model definition and purpose, theoretical assumption, input data, risk capture and robustness, suitability and applicability, and validation and verification were critically explained and analysed. In view of the above discussion, the next chapter reviews the existing cost models against the model requirements discussed in section 3.2 and justifies the choice of Bayesian method and activity based costing (ABC) as the most appropriate method for this study in view of the research gap identified.

Chapter Four

REVIEW OF COST MODELS AND JUSTIFICATION OF BAYESIAN METHOD

4.1 Introduction to cost estimation methods/techniques

In today's competitive global market, the survival of companies is dependent on the ability to deliver projects in a shorter time, at less cost and with a reasonably high level of quality. Cost is the most significant factor in project delivery in the offshore deep-water drilling sector as failure to develop a reliable cost estimate can generate both cost overrun i.e. when there is underestimation and cost underrun i.e. when there is overestimation which are affecting project delivery schedule (Naizi *et al.* 2006). Whereas cost underrun rarely happens in offshore drilling projects, overrun is a common phenomenon as 9 out of every 10 projects overrun their costs (Poiate *et al* 2006, Enshassi *et al.* 2009, and Yang & Wei 2010). Hence the reason for this research. There are many definitions of cost estimation; it was described as a prediction of project cost by Aderoba (1997) or as a method that forecasts cost of project activities before their physical execution (Shahab & Abdalla 2001). H'mida *et al.* (2006) defined cost estimation as the art of forecasting the cost to execute a project or to make a product. Again, the Association for Advancement of Cost Engineering (AACE) defined it as "the determination of quantity and the predicting or forecasting, within a defined scope, of the costs required to construct and equip a facility, to manufacture goods, or to furnish a service" (AACE 1990). The researcher defines cost estimation as a technique used to forecast the cost of projects before execution by synthesising the best and most appropriate definitions given by other authors above. Table 4-1 shows a summary of the definitions of cost estimation of which the researcher's definition was derived.

Table 4-1. Definitions of cost estimation

Author Year	Cost Estimation Definition
AACE (1990)	The determination of quantity and the predicting or forecasting, within a defined scope, of the cost required to construct and equip a facility, to manufacture goods, or to furnish a service.
Aderoba (1997)	Prediction of project costs.
Shehab and Abdalla (2001)	Cost estimation was explained as a method that forecasts cost of project activities before their physical execution.
H'mida *et al.* (2006)	Cost estimation as the art of forecasting the cost to execute a project or make a product.
Tammineni *et al.* (2009)	Cost estimation is the process of forecasting the product cost prior to execution of any product development stages.

It is essential to understand the difference between cost accounting and cost estimation as it is misconstrued to mean the same thing. Cost accounting measures a project/product cost after execution of a task/activity/project while "cost estimation is concerned with cost control, business planning and management science, including problems of project management, planning, scheduling, profitability analysis of engineering projects and processes" (Roy 2003:1). Hence cost accounting identifies actual cost of resources used while cost estimation relies on cost accounting and other cost data to predict the future cost. Cost estimates are used for several functions in different companies which include; project cost control, cost management, budgeting, decision making, and negotiation (Ben-Arieh 2000, Roy 2003, and Garcia-Crespo *et al.* 2011).

There are different techniques that can be used for project cost estimation. Each of the cost estimation techniques has its strength, weakness, and area/situation where the maximum accuracy can be derived. It is therefore important to carefully select the appropriate cost estimation method or technique for a project as it largely determines the reliability of the cost estimate (Franke 1987, Cooper *et al.* 1985, Laufer 1991, Berny & Townsend 1993, Wang & Haung 2000, Artto *et al.* 2001, Wang 2004, Chou *et al.* 2006, Naizi *et al*. 2006, PMI 2008, and Chou 2009).

In view of the above argument, the researcher analyses types of cost estimation techniques in the offshore deep-water drilling industry in other to choose the appropriate one to address the research problem. Generally, cost estimation techniques can be grouped into 3 types which includes quantitative, qualitative and mixed method (Chou *et al.* 2006, Naizi *et al*. 2006, PMI 2008, and Chou 2009). Currently in the oil and gas industry, 5 classifications of cost methods have been found under the quantitative Franke (1987), Cooper *et al.* (1985), Laufer (1991), Shehab & Abdalla (2001) and Roy (2003), 3 for mixed methods Berny & Townsend (1993), Wang & Haung (2000), Niazi *et al.* (2006) and 4 for qualitative Artto *et al.* (2001), Wang (2004), Tammineni *et al.* (2009). The 12 categories have been summarised in figure 4-1 below and in-depth analysis and discussion for each has been provided in the subsequent sections. Examination of the differences in categorisation by different authors was pursued and argument and justification for the choice technique and category of cost method adapted by the researcher has been offered.

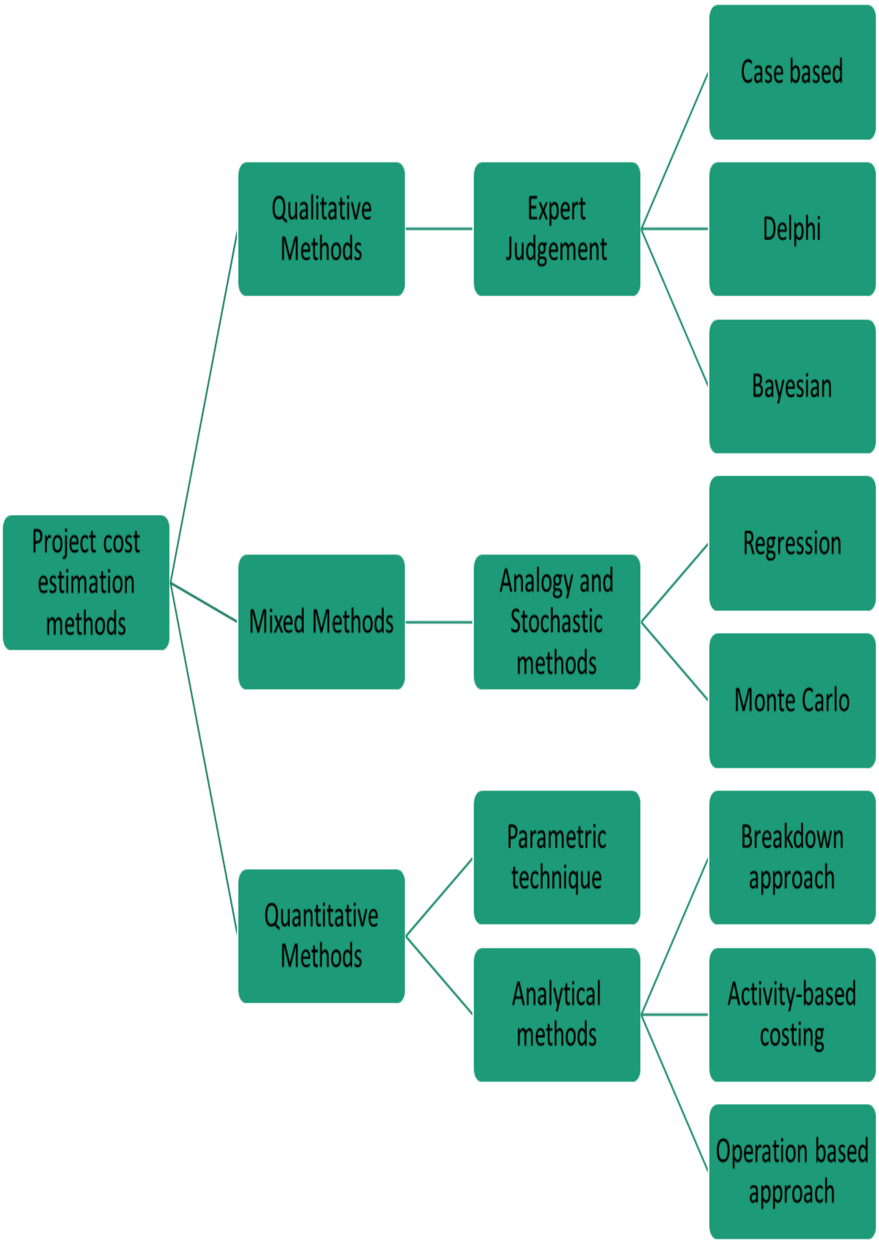


Figure 4-1 Classification of cost estimation methods (Roy 2003, Naizi *et al.* 2006, and Tammineni *et al.* (2009).

The next sections comprehensively analyse relevant cost estimation models for the oil and gas industry as listed in figure 4-1. The strengths and weaknesses of each model are discussed and justification of the choice of a Bayesian approach for this work is explicitly highlighted.

4.2 Quantitative Methods

4.2.1 Parametric technique

The parametric cost estimation technique involves the use of certain project parameters or variables to develop a relationship with cost (Roy 2003, Qian & Ben-Arieh 2008). The parameters used in the cost estimation do not necessarily guarantee accurate project estimates completely (García-Crespo *et al.* 2011). Roy (2003), and Qian & Ben-Arieh (2008) gave examples of these parameters as volume, weight, number of inputs-outputs etc. In the method of scales, a cost to parameter ratio is developed using the most important parameter identified by the estimator (Roy 2003). Statistical models on the other hand employ historical information using statistical techniques to establish a relationship between cost and cost parameters whereas in cost estimation formulae, a mathematical relationship is developed to connect cost with parameters (Qian & Ben-Arieh 2008). Naizi *et al.* (2006), and Qian & Ben-Arieh (2008) explained that the parametric method is simple and easy to use when the project is completely defined and has the potential to give excellent cost estimates when accurate data are collected and assumptions clearly documented. Roy (2003), and García-Crespo *et al.* (2011) argued that in cases where large numbers of parameters exist, complex mathematical relationships need to be developed to ensure accuracy in cost estimates.

A parametric estimation method was adopted by Collopy & Curran (2005) using statistical analysis techniques to find correlations and relationships between cost drivers and other cost parameters in casing scheme (is large diameter pipe that is assembled and inserted into a recently drilled section of a borehole and typically held in place with cement) when drilling. The accuracy of cost estimate is achieved in casing during offshore drilling when well pressure is known but reduces drastically when pressure complexity increases. Collopy & Curran (2005) proposed the integration of models as a step towards attaining improvement in offshore drilling cost estimation. A cost model that integrates activity based costing (ABC) with parametric cost estimation techniques was developed by Ben-Arieh (2008) to estimate the cost of machine failures during drilling operations. The results showed that the developed model was more accurate (approximately 65%) than traditional cost models which has accuracy level of below 50% in relation to the actual project cost. The two models discussed earlier covered an activity in the entire drilling process but there is no further evidence suggesting that using any of this model for the other activities in the offshore drilling process can guarantee accurate project cost estimates. Colmer (2005) argued that as much as parametric and statistical models may be good approaches to cost estimation, the ability to reduce cost overruns goes beyond establishing correlations and relationships between cost parameters and therefore proposed combinations of several models to tackle the problem of cost overrun.

4.2.2 Analytic methods

Analytical cost estimation techniques adopt the use of fundamental units of projects and analyse each unit cost and finally aggregate all units cost (García-Crespo *et al.* 2011, and Niazi *et al.* 2006). These techniques require detailed analysis of process and project parameters and accurate information before any reasonable estimate can be made. Operation based approach, activity-based costing (ABC) and breakdown (Bottom up) approach are the classification of analytical technique that have been explained in the following section.

4.2.2.1 Activity based costing (ABC)

Activity-based costing (ABC) is defined as the process of identifying activities essential to developing a product or executing a project by finding the cost associated with each activity (Ben-Arieh 2000, Niazi *et al.* 2006, Qian & Ben-Arieh 2008, Yongqian *et al.* 2010, and García-Crespo *et al.* 2011). ABC thrives on the project principle that “cost objects utilise activities and activities consume resources” (Yongqian *et al.* 2010). The usage and implementation of ABC is very simple which makes it suitable and applicable to any industry. Ben-Arieh (2000) suggested a seven step procedure to follow when applying ABC these are to; “identify activities; identify cost centres; analyse indirect costs and calculate their cost-driver’s rates; assign resources to each cost centre and determine cost centre driver rates; analyse each activity and find the total cost for each activity; define activity drivers for each activity and find activity cost-driver rate; and finally estimate the cost of new parts via activity cost-drivers spent”. This approach is found to be very helpful in providing accurate and traceable cost information and is flexible enough to be adapted in any process or system (Ben-Arieh 2000, Niazi *et al.* 2006, Qian & Ben-Arieh 2008, and Yongqian *et al.* 2010).

Operators in the oil and gas industry rely heavily on activity based costing (ABC) since it is easy to formulate if accurate data is kept on all activities (Zhang *et al.* 1996, and Yongqian et al. 2010). It was suggested that when cost estimators observe overheads of project activities in related projects to create a cost estimates for future purposes, ABC becomes very useful in that process. This is because ABC can store historical data on cost drivers which are used to predict the cost of future project activities (Zhang *et al.* 1996, and Yongqian *et al.* 2010). However, it becomes difficult to use if there is no useful related information on a new project which is one of the reasons cost overrun persists in the industry. Brimson (1998) argued that ABC is best used to optimize and identify activities that have potential to increase project costs. In relation to the offshore drilling operations, ABC is highly rated because of the depth and details it offers in terms of allocation of cost to project activities. Despite that, the risk capture and robustness of ABC to estimate drilling cost accurately is questionable as it does not have any in built risk identification systems (Ben-Arieh 2000, and Niazi *et al.* 2006). It can be debated that the purpose for which ABC was developed was to help trace cost activities for projects which it does hence, model builders need to build in measures that can improve the risk capture and robustness to meet the challenges of the industry in which it is used. Since risk is about perception and ABC on its own cannot predict risk (Xiaotie & Miao 2011 and Dongkun & Xu 2012), the prospect of combining ABC with an expert judgement is perhaps the possible way to effectively solve the problem of cost overrun in the offshore drilling industry.

4.2.2.2 Operation based approach

Niazi *et al.* (2006) defined the operation based approach as the process of identifying the operational requirements of a project by allocating cost to all the activities needed to complete the project. Findings by Niazi *et al.* (2006), and García-Crespo *et al.* (2011) have shown that this process helps to analyse actual operation time and non-operational times such as setup time and waiting time etc. into cost estimates. Additionally, Curran *et al.* (2008) discussed that the cost of drilling time, debris removal time, maintenance and rig cleaning, and other operational activities in drilling can be accurately determined using this approach. A comparison of this process with ABC earlier discussed reveals a lot of similarities in terms of the analytical methods and the process of cost allocation hence it would not be farfetched to argue that the operation-based approach is an extension of ABC that is suitable for analysing process time in projects (Fuchs *et al.* 2008). Again, because of the enormous detailed data demands and time required for gathering such data, Niazi *et al.* (2006) argued that it is may be a suitable approach for smaller projects but impracticable to use for complex projects where many activities are involved such as the oil industry. For example, to prove the findings of Niazi *et al.*, Choi *et al.* (2007) developed a knowledge based model using operation based approach to test its ability to improve decision making in offshore drilling project. The results revealed that the model has the capability to support drilling decision making to reduce cost. Owing to the fact that offshore deep-water drilling involves complex activities, it demands the use of an equally robust method to be able to adequately and comprehensively estimate project costs which is lacking in this process making it unsuitable to use in this study

4.2.2.3 Breakdown (Bottom up) method

Bottom-up methods describes the use of data from several activities to arrive at a bigger project/product picture (O'Connor *et al.* 1993). This method is largely regarded to be based on pure perception where cost estimate of projects is arrived at through a detail cost of specifications and requirements in each project subsystem (O'Connor *et al.* 1993). Bottom up models have been used to optimize production profiles of different oil reservoirs in different regions with varying reservoir dynamics and economic scenarios (Jorgensen 2004). However, there is no proven evidence in literature that portrays that bottom up method has on its own or jointly with other method been used to estimate cost in the offshore industry. Niko *et al.* (2013) argued that the bottom up method often has significant inadequacies since they are single-issued which can hinder the planned outcomes of projects and give impetus for cost escalation (Dale 1995, Mohammad 2012). Henrik (1998) noted that this method lacks rigor, robustness and ability to factor in risk and hence raised concern of its suitability.

Generally, the bottom up method does not seem to have the capability to stand alone in managing cost related overruns unless integrated into a more robust model.

4.3 Mixed Method (Quantitative and Qualitative)

4.3.1 Analogy and stochastic

Analogical and stochastic cost estimation techniques estimate project costs by identifying the costs of previously executed projects (Maybeck 1979, García-Crespo et al., 2011; Niazi *et al.* 2006). The value of these techniques is reliant on the obtainability of past data (Trogensen & Wallace 2000). The importance of Analogy and stochastic techniques to generate cost estimates using previous quotes of similar projects in the oil industry was examined and it was concluded that lessons from previous projects have the potential to inform future estimates (Jainendra (1990). For example, the analogy and stochastic based model used in one of the Norwegian oil fields confirmed the relevance of learning from past projects with similar features as the data helped in the progression of the oil field development. In fact, the model disclosed that the reservoirs features and hydrocarbon descriptions were vital in enhancing the cost estimation of the project and its success (Kevin *et al.* 2007). It has been argued that every project is unique in its own right in terms of the risk, purpose, costs and benefits therefore, having a reference point or past data on previous projects is a good starting point for improving current projects operations (Aurelie & Chris 2008). Two of the techniques relevant to the offshore industry, regression and Monte Carlo, are reviewed below.

4.3.1.1 Regression

Regression analysis is one of the most powerful statistical tools that has the ability to analyse and predict the contribution of project variables to the overall estimate reliability (Skitmore & Patchell 1990, and Tam & Fang 1999). In regression, historical cost data is used to establish relationship between project cost and project variables and that relationship is then used to estimate the cost of a similar project (Niazi *et al.* 2006). Two regression analysis methods are used, which are forward selection and backward elimination as discussed by Ciurana *et al.* (2008). While forward selection adds the independent variable with the highest impact on model prediction ability in every step of the analysis, backward elimination eliminates independent variables with lowest contribution to the model in each step of the modelling (Niazi *et al.* 2006). Ciurana *et al.* (2008) recommended the use of regression for making project cost estimates because of its well defined mathematical basis. It has however been challenged by Garza & Rouhana (1995), Adeli & Wu, (1998), Bode (1998), and Bode (2000) that regression analysis lacks a clearly defined approach that should help estimators select the best cost estimating application that fits given historical data. More so variables with greater influence are required to be reviewed in advance before opting for this analysis and the difficulty in using large number of input variables makes it unsuitable for projects with such characteristics (Bode 1998, 2000, and Smith and Mason 1997).

There is therefore no doubt about the capabilities of regression analysis for estimation in fields such as marketing, medicine, manufacturing and therefore its appropriateness would be tested in section 4.5 to determine its adaptability for this study just like all the other models discussed and the ensuing models.

4.3.1.2 Monte Carlo

Another cost estimation technique that has been used in the construction industry is the Monte Carlo simulation. Its ability to assess the interdependence of risk and cost of projects makes it ideal to use in larger engineering projects (Dorp & Duffey 1999).

As a rule, the Monte Carlo technique is designed to answer “what is?” problems (Dorp & Duffey 1999) based on realistic assumptions of events or projects. Mainly, the ability to cover risk, complexities and create adequate allowance for uncertainties in construction projects by Monte Carlo is makes one of the preferred project costing methods in the oil industry. However, the assumption of statistical independence of project activities by Monte Carlo has been debated as a weakness of the model (Van Dorp & Duffey 1999). Cortazar & Schwartz (1996) particularly pointed out the failings of a simulated Monte Carlo model when considering dynamic correlations, relationship and interactions between risk events to be a big setback to the model. Similarly, Lima & Suslick (2006) used Monte Carlo to assess the interference between global oil price volatility and 12 offshore upstream projects volatility using the cash flow of the projects rather than historical oil prices data. The results showed that the volatility of the 12 offshore projects can devalue global oil price by 79% whereas there was no evidence to support that volatility of oil price can undervalue any of the projects considered (Lima & Suslick 2006). Not much has been published on the use of Monte Carlo for cost estimation in the oil industry, notwithstanding, the techniques for the model is critically analysed in 4.5 to see if its best option to use to provide accurate offshore drilling cost estimates.

4.4 Qualitative Methods

4.4.1 Expert Judgement

From the foregoing, there is now no doubt that cost estimation is one of the difficulties facing the oil industry. In context of this difficulty, expert judgement is seen to have a role to play in finding an appropriate method to accurately predict project costs because of the additional strength it provides when and where data limitations exist

(Idrus *et al.* 2011). Expert judgment techniques consist of using the expertise and experiences of cost estimation experts or a group of experts on a planned project to determine its cost (García-Crespo *et al.* 2011, and Niazi *et al.* 2006). Knowledge is stored in the form of probability, judgements, decision trees, rules etc. using this technique which can be used to estimate current or future costs of projects (Niazi *et al.* 2006). Examples of expert judgement techniques used in the oil and gas industry are case-based approaches, Delphi and Bayesian approach.

4.4.1.1 Case Based approach

A case-based technique relies on the results of preceding cost estimation cases to predict the cost of a project with the same features (Roy 2003, Niazi *et al.* 2006, and García-Crespo *et al.* 2011). Roy (2003) described it as an artificial intelligence technique because data is stored and reused in a more structured way to explain cost of unknown problems in projects. The process of the case-based approach involves: (1) defining a new case (problem), (2) choosing similar case from historical data base using a measure of similarity, (3) adopting or modifying preceding case, (4) testing and evaluating the solution, and (5) documenting new results in data base for future use (Duverlie and Castelain 1999). Roy (2003), and Niazi *et al.* (2006) acknowledged that case-based approach helps to develop a rough estimate of project costs relatively easily and quickly and the quality of cost estimate is highly dependent on the similarities of precedent cases. However, Roy (2003) argued that depending on precedence cases for estimating cost of innovative products, offshore projects, railway and other capital intensive projects may not be reliable because of lack of past data on all project activities and differences in project scope and function.

A cost estimation system using a case-based approach was integrated into an algorithmic model by Mansour *et al.* (2011) to enhance accuracy in project cost estimation for the oil and gas industry. The model could revise, reuse, and retain data but lacked the ability to quantify experiences and expertise of the experts for future reference (Mansour *et al.* 2011). The weakness in this model suggests there is a need for an improvement in the way experiences are quantified into the model. Wang & Meng (2010), combined a case-based approach with ABC to estimate cost of project components. Their results showed that the proposed model could offer support in make or buy decisions and not in cost estimations. It is therefore clear from the discussion that, a case-based cost estimation functions best when reproducing the cost of a project with the same similarity to guarantee reasonable cost estimates, and since there exist significant differences in offshore drilling projects, such a requirement is unlikely to be met, thereby making this approach difficult to use in the context of the current research.

4.4.1.2 Delphi

The Delphi technique is a popular group consensus technique noted for expert judgement (Wild & Torgersen 2000). This provides the platform for in-depth exchange of ideas, expertise, knowledge and volume of information needed to improve cost estimation of projects (Wild & Torgersen 2000). The wideband Delphi Technique (technique for estimating effort) has successively been used in a number of studies and cost estimation activities and has shown impressive results (Idrus *et al.* 2011). Expert judgement offer valuable space to factor in differences in past project experience and proposed projects requirements (Niazi *et al.* 2006, García-Crespo *et al.* 2011, and Idrus *et al.* 2011). There is allowance to integrate new technologies and exceptional personnel expertise which no other model can simulate precisely (Polat & Bingol 2013). Delphi employs an iterative approach that focuses on the elicitation of joint/aggregated opinions from experts in the bid to improve the accuracy of estimates and predictions (Van de Ven & Delbecq 1974). García-Crespo *et al.* (2011) and Idrus *et al.* (2011) argued that the two stage process approach for Delphi which is to firstly select a small panel of experts from different backgrounds to provide answers to a survey and their aggregated judgments subsequently given to a different set of small panel group to review and finally provide answers to a second set of questions before a consensus is finally reached makes it difficult to use in cost estimations. It may be difficult for the second set of experts to ascertain the reasons behind the opinions formed by the first experts as there is no guarantee that either of them is right. This brings into question the principle behind the Delphi process as an expert with a higher position could use this to veto decisions which can create biases. Moreover, in context to the research problem, Delphi process may not be appropriate to use at this time as there is no evidence in the literature to support its ability to generate any form of probabilistic data using opinions collected both in theory and practice (Congdon 2001).

Notwithstanding, Delphi has widely been used in thousands of studies since it was developed in the early 1950s, notably in the fields of technology (Patari 2009, and Rikkonen & Tapio 2009), marketing (Jolson & Rossow 1971, and Best 1974), health care (McKenna 1994, Cantrill *et al.* 1996, Wild & Torgersen 2000, and Keeney *et al.* 2001), finance (Muradoglu & Onkal 1994, and Onkal & Muradoglu 1996) and education (Putnam *et al.* 1995 and Clayton 1997). One of the strength in the first stage of Delphi elicitation is that participants are denied the opportunity to discuss each other's ideas which helps to stop dominant personalities taking control however this is compromised in the second stage as new set of experts can discard view of earlier expects (Fitch *et al.* 2001). Again, Dalal *et al.* (2011) critiqued the use of Delphi as outmoded owing to the fact that there are limitations to the number of experts to be recruited. While 50-100 experts are considered ideal when using computer-based Delphi studies (Turoff *et al.* 2006), only 5-20 are recommended for paper-based (Rowe & Wright 2001). Though Wild & Torgersen (2000) claimed that Delphi has the capacity to accommodate 300-500 experts, there is no evidence in literature to support this assertion.

While the modern Delphi technique has included the use of face-to-face discussions it is still argued to suffer from the deficiencies of the Nominal Group Technique (NGT) (Fitch *et al.* 2014). NGT was designed to identify and evaluate problems and ideas whereby the basic Delphi structure is adopted in an approach called estimate-take-talk-estimate technique which ensures participants ideas are discussed in rounds of estimation (Rowe & Wright 1999 and 2010). Bartunek and Murninghan (1984) argued that NGT is suited for small panel size where as part of the steps, participants generate individual judgements. Secondly, as part of the steps, a collection list of all the individual ideas are gathered in a round-robin fashion where members are required to finally vote independently on priorities of the ideas for the group (Van de Ven & Delbecq 1974, Bartunek & Murninghan 1984, and Dalal *et al.* 2011). The NGT has however been criticized to be too costly, time consuming and difficult to convene due to geographical barriers (Rowe & Wright 2010). Hackman & O'Connor (2004) argued that consensus is not easy to attain in face-to-face interactions involving more than ten participants as there are tendencies of "force compromise" and "free riding" i.e. inactive participants. Hence, as with preceding models, the problem of Delphi is its lack of ability to generate probabilistic responses into models to improve cost estimation and the potential inherent biases in its process. Therefore despite its potential there is little evidence to justify its use in this study.

4.4.1.3 Bayesian approach

The Bayesian method or probabilities uses “degrees of belief” to represent probability of opinion in an orderly approach to enable inferences of data to be made through the revision of past opinion in the light of new relevant information (Berry 1996, Lee 1997, and O’Hagan & Luce 2003). Thus Bayesian probability assigns quantity to represent a state of knowledge or a state of belief (O’Hagan 1994 & Congdon 2001). A major distinction between Bayesian and other form of probability is that whereas hypothesis is tested without being given a probability under sampling inference/probability (predetermined number of observations are taken from a larger population) hypothesis is assigned a probability in the view of Bayesian (O’Hagan 1994 & Congdon 2001). Hence Bayesian is best used to solve for an unknown when a known variable or probability is given and applied with new knowledge and information. O’Hagan (1994) discussed that Bayesian methods employ the use of random variables to model unknown quantities in statistical models which includes the use of current knowledge about model parameter to present a probability distribution called the “prior distribution” which can be expressed as:

$$P(\theta)$$

Given the current knowledge for the prior distribution $P(\theta)$, the posterior(probability) of a new variable for example (y) can be predicted. This occurs when new relevant data about the parameter (y) is available, the prior probability distribution $P(\theta)$ of the model is then updated with the “likelihood value” of the observed distribution data given the model parameters which is written as:

$$P(y|\theta).$$

The prior is then combined with this new information to produce an updated probability distribution called the "posterior distribution" which forms the basis for every Bayesian inference (O'Hagan 1994, and Congdon 2001). When more data becomes available, the posterior distribution is calculated using the Bayes' formula with a given prior data. Bayes formulae is expressed mathematically as:

$$P(\theta|y)=p(\theta)\times p(y|\theta)/P(y)$$

Which means the posterior is proportional to the prior times the likelihood where (θ) is an uncertain event and (y) the new information obtained or learnt after (y) has occurred. Hence P(θ) the prior probability while P(y) is the posterior distribution which explains the resultant knowledge learnt before and after the occurrence of y (Garthwaite *et al.* 2006). Bayes Theorem uses sequential analysis techniques (does not have fixed sample size but evaluates data as and when collected) to update prior and posterior distributions when "beliefs or knowledge" changes.

The application of the Bayesian approach is varied and there is no clearly defined types except that the use of Bayesian is much emphasized on the use of the Bayes rule as a foundation (Jenson 2007). An application which is argued to be efficient in modelling operations and cost in different industries known as the Bayesian Networks or probability networks is worth considering in the context of this study because of the interdependencies's in the variables that cause cost overrun (Chan 1998, Lo *et al.* 2006, Acharya *et al.* 2006, Shahriar *et al.* 2012, and Zheng *et al.* 2014). Bayesian network shows conditional probability ("the probability of an event occurring given that another event has already occurred") and causality relationships between variables and the joint probabilities of all the variables occurring at once. It employs directed acyclic graph using nodes and arcs to represent variables and the conditional dependencies between them and their combined probability impact on the parent node (issue which the variables seek to address) (Jenson 2007, and Fenton 2015). While the nodes represent variables, arcs are used to establish the relationships between the variables and their overall impact on the model in question (Fenton 2015). Bayesian Networks are powerful tool for representing unknowns or uncertainties using historical knowledge or data and provide analysis on the cause and effects of variables in a model (Jenson 2007). Again, probabilities calculated using judgements from historical events have the ability to predict the future through Bayesian Networks.

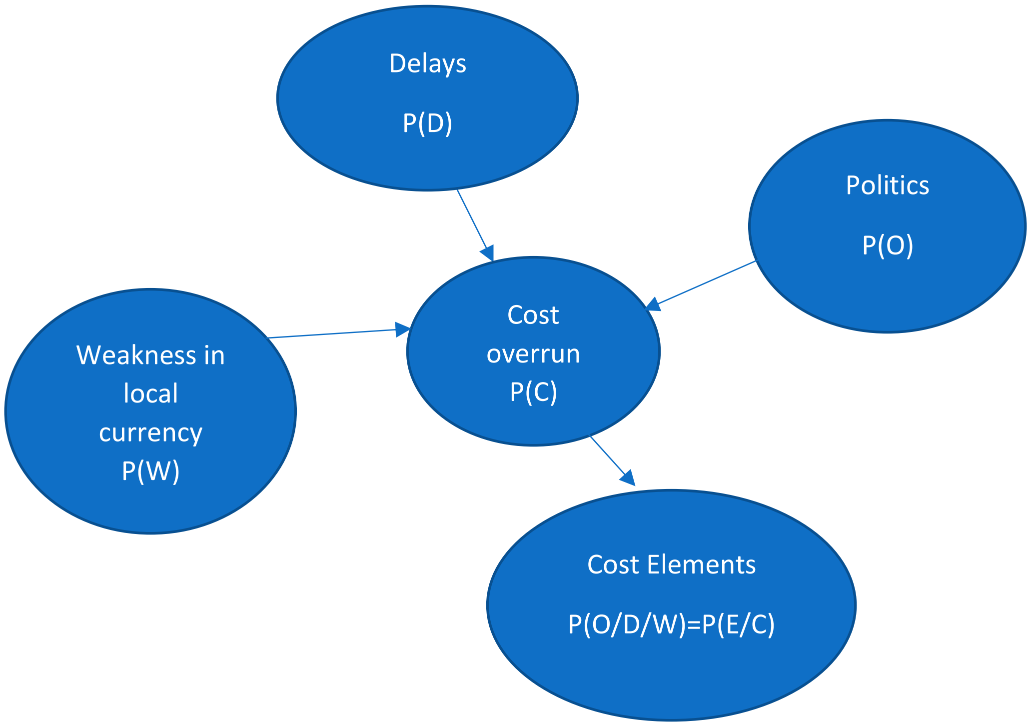


Figure 4-2: Offshore drilling cost estimation Bayesian network example

Figure 4-2 above shows how Bayesian Networks can establish the relation between delays, politics and weaknesses in local currency against the US dollar and cost overrun by calculating for the individual probabilities as given by P(D), P(W) and P(O). Using the probability distributions of the three cost drivers i.e. P(D), P(W), and

P(O), their effects on drilling cost elements can be calculated by finding the conditional probability of the 3 variables on the cost element.

The conditional probability of an event W is the probability that the event will occur given the knowledge that an event D has already occurred. This probability is written P(W|D), as the notation for the probability of W given D. Where events D and W are independent (occurrence of D has no effect on the probability of event W), the conditional probability of event W given event D is simply the probability of event W, that is P(W). If events D and W are independent, then the probability of the intersection of D and W (probability both events occurring) is defined by P(D and W) = P(D)P(W|D). From this definition, the conditional probability P(W|D) is easily obtained by dividing by P(D) which is P(D)P(W|D)/P(D). To calculate the probability of the intersection of more than two events as in the case of figure 4-2 above, the conditional probabilities of all of the preceding events must be considered (O'Hagan 1994, and Congdon 2001). In the case of three events, as shown in the figure 4-2; O, D, and W, the conditional probability is P(O and D and W) = P(O)P(D|O)P(W|O and D) or P(O/D/W). The validity of the Bayesian Network and its probability distribution is dependent on the probability distribution of each of the nodes and the reliability of the prior knowledge (Niedermayer 1998). The importance of Bayesian approach to industries and research has been well reported in literature.

O'Hagan (1994), Berry (1996), Congdon (2001), and Garthwaite *et al.* (2006) recommended the use of Bayesian approach in making sound decisions in the face of data limitation and uncertainty because of its philosophical consistency. However, David & Baglioni (1988), Carlin & Thomas (1997), and Gelman *et al.* (2014) have criticised the prior probabilities used in Bayesian as intrinsically subjective among individuals and as such represents a fundamental flaw. O'Hagan (1994), Congdon

(2001), and Garthwaite *et al.* (2006) argued that every statistical method that relies on inference is bound to have different subjective choices but that the rationale and consistency of those opinions must be protected, which is a core requirement for Bayesian methods. Bernardo (2003) maintained that the Bayesian approach is suitable for cost estimation when there is data limitation and as such the issue of biases can be reduced by using a more robust and comprehensive elicitation process in collecting the prior estimates. Furthermore, many disciplines with large and complex statistical problems have adopted Bayesian methods as it yields direct and intuitive answers to the practitioner's questions (O'Hagan 1994, Congdon 2001, Garthwaite *et al.* 2006). According to Bernardo (2003) the Bayesian method answers the challenges under the decision making process and most statistical inference. It also provides a complete paradigm for the approach required to tackle uncertainty comprehensively. Thus the use of Bayesian offer better 'rational and conditional measure of uncertainty' in estimations (Bernardo 2003).

A review of the use of Bayesians approach in the various industries by past researchers provide further insights on the weaknesses, strengths and applicability of this method to a particular research problem. Lecklin *et al* (2011) used a Bayesian method to analyse the biological effects of oil spills caused by accidents in low-saline Gulf of Finland. The study considered some selected organisms with subsequent subgroups and their response to oil exposure. The model proved that impacts of oil spill in the Gulf of Finland is minimal irrespective of the volume of oil spilled. However, it confirmed that auks and ducks are the most vulnerable in cases of spill while amphipods, gull and other littoral fishes delay in their recovery in situations of oil spill in the Gulf of Finland (Lecklin *et al* 2011). This evidence proves that the Bayesian approach works and the findings is also relevant to this work because it has shown the ability of Bayesian to establish and determine impact and effects between variables as required for this study. Again, other evidence supporting Bayesian is an initial result from a study that measured greenhouse gas emissions from selected farms in the United Kingdom which showed that using a Bayesian method provided a better understanding of how activities on farms could affect the environmental conditions through the emission of greenhouse gas (Perez-Minana 2012). Silver and Costa (2012), developed a cost model based on a Bayesian approach to estimate the cost of oil projects in Seoul using past project information. It was concluded from the findings that a Bayesian approach has the ability to improve project estimation when combined with an appropriate cost model. This suggests that the debates in the literature regarding the ineffectiveness of a single estimation method or technique (qualitative or quantitative) to accurately produce cost estimates is most likely valid.

Another example of the use of the Bayesian method was seen in the work of Assaf *et al.* (2011) which compared the cost estimate of Japanese steam power generation companies with other cost models and found that restriction of CO_2 emissions was a potential strategy for reducing total cost for the steam power companies. It was concluded that a Bayesian method is an appropriate approach for cost estimation because of the inbuilt learning cycle that gives the opportunity to improve cost estimates with new knowledge or data. Khatibisepehr *et al.* (2013) predicted the time and cost of offshore pipeline projects by developing a Bayesian inference model which adopted historic data on pipeline instrumentations in the oil and gas industry. Results showed more than a 20% improvement in cost estimates compared to the use of parametric techniques. This evidence indicates the potential of Bayesian Networks as an appropriate technique worth exploring as a solution for cost overrun in the offshore deepwater drilling industry. As discussed earlier by Maybeck (1979), García-, Niazi *et al.* (2006) and Crespo *et al.* (2011) about the need to integrate two models, the next section 4.5 provides analysis of the quantitative cost estimation techniques ideal to be used with a Bayesian approach.

4.5 Analysis of cost estimation models

It can be inferred from the review of extant literature that no single estimation technique or model has the ability to eliminate cost overruns in the offshore drilling industry because of data limitations, high risk and the need to make models applicable to the system and operations of the industry (Mansfield *et al.* 1994, Han *et al.* (2009), Chou 2011, and Chaudry *et al.* 2013). The motivation of this study as shown in section 1.6 was to investigate if combining a Bayesian technique with a cost model would yield better results. In view of this, this analysis justifies why ABC is best suited to be integrated with Bayesian Network technique in section 4.7. The table 4-2 below assesses the quantitative cost estimation techniques based on their strengths and weaknesses as reviewed in the literature. Based on the above analysis and the summarised strengths and weaknesses of the models in table 4-2 below and in the context of the scope of this research, the appropriateness of integrating ABC cost model with Bayesian Network approach to form a single cost estimation model was argued. Further discussions on the justification of the model choice is critically analysed in section 4.7 of this chapter.

Table 4-2 Quantitative cost estimation techniques analysis

Cost estimation method	Weaknesses	Strengths
Parametric References: (Roy2003, Qian Ben-Arieh 2008, García-Crespo *et al.* 2011)	1. establishing relationship is not enough for a good cost model 2. risk and complexity of drilling project make it hard to define completely 3. require complex equations when large data is used	1. ability to establish correlation and relationship 2. simple to use when project is clearly defined
Activity-based costing (ABC) References: (Zhang *et al.* 1996, Niazi *et al.* 2006, Yongqian *et al.* 2010)	1. There is no in-built risk capture	1. provide cost traceable information and is flexible to integrate with other models 2. suitable and applicable to the operation of the offshore drilling industry 3. model has the capability to support drilling decision making to reduce cost
Operational based (Fuchs et al. 2008, Choi et al. 2007)	1. Is time consuming 2. Not proven in the oil industry 3. Focusses on only internal process with little attention for external factors	1. Provide detail analysis of cost for each phase of project
Breakdown approach	1. Is single-issued based which has potential for inadequacies	1. Suitable for optimization exercise when

References:(O'Connor et al. 1993, Dale 1995, Mohammad 2012, Henrik 1998)	2. Lacks rigor 3. Require additional tool for analysis before results van make sense	there is a known results/outcome 2. Suitable for small projects

It can be seen from the above table 4-2 that each of the cost estimation techniques has unique abilities and some inadequacies. Parametric, Operational based and Break down approaches have been argued to either lack the ability to establish relationships between variables or untested in large and complex projects which make them difficult to use among the other weaknesses listed above (O'Connor *et al.* 1993, Dale 1995, Zhang *et al.* 1996, Henrik 1998, Niazi *et al.* 2006, Yongqian *et al.* 2010 Fuchs *et al.* 2008, Choi *et al.* 2007, Mohammad 2012). It is the Activity Based Costing (ABC) that has a proven record in the oil and gas industry and seems to be a good compliment to the Bayesian in terms of integrating them. Again, the only limitation of ABC listed in the table above can be covered by Bayesian as it is a problem of risk capture which is a matter of probability ably covered under Bayesian (Niazi *et al.* 2006, Yongqian *et al.* 2010).

4.6 Research Gap Analysis

The main research gap identified from the reviewed literature in section 1.3, chapters 2, 3 and 4 is the lack of a validated framework that can provide accurate estimations with limited data, or one that can precisely capture risk and/or factor probability results of all the cost variables in the offshore deep-water drilling operations into a model and can be suitable and applicable to the systems and operations of the industry. To attempt to fill this gap, analysis of requirements for a cost model in the oil industry was done in chapter 3 to serve as the basis on which past and current models can be evaluated and critiqued. This chapter has analysed the relevant cost models and concluded on the need to integrate ABC (quantitative approach) with Bayesian Network (qualitative approach) based on their strengths and weaknesses. A justification of this choice is provided in the next section.

4.7 Justification of Bayesian and ABC techniques

The Bayesian approach to statistical inference has been described as the explicit quantitative use of experience, expertise and skills in the analysis and interpretation of cost estimation evaluation (Fryback *et al.* 2001, O'Hagan and Luce 2003, Spiegelhalter *et al.* 2004, and Ades *et al.* 2006). From the forgoing discussion of Bayesian approaches in section 4.4.1.3 and the research gap analysis in section 4.6, it has been demonstrated that Bayesian analysis has an important feature of permitting the incorporation of expert opinion in the form of prior distributions. Making decisions or giving prior distributions under uncertainty requires the use of parameters. This makes ABC technique an appropriate model combination option with the Bayesian because it provides traceable information on activities of drilling which can serve as the prior and it is also suitable and applicable to the operation of the offshore drilling industry making. Thus the use of parameters, processes and procedures for costing can easily serve as the parameters on which probability distributions can be given using Bayesian (Felli and Hazen 1999, O'Hagan & Luce 2003, Spiegelhalter *et al.* 2004, and Ades *et al.* 2006). Owing to the cost estimation model requirements discussed in section 3.2 in chapter 3, it emphasised the need for improvement in the internal validity to guarantee the generalizability and reliability of such model. As such, since standard probabilistic sensitivity analysis is essentially Bayesian, it makes this approach engaging as it is satisfactorily flexible to enable suitable allowance to be made for all risks associated with cost variables for offshore drilling projects and can be easily integrated with other decision modelling frameworks as in the case of ABC (Cooper *et al.* 2002, Parmigiani 2002, Cooper *et al.* 2004, Qian & Ben-Arieh 2008, Yongqian *et al.* 2010, and García-Crespo *et al.* 2011).

Another rationale that justifies the choice of Bayesian and ABC is the fact that there are evidences that suggest these two can offer better solutions compared to the exiting cost models as discussed in sections 4.2, 4.3 and 4.4 (O'Hagan 1994, Congdon 2001, Garthwaite *et al.* 2006, Jenson 2007, Gelman *et al.* 2014, and Fenton 2015). Again, because the common limitation of most of the past models is their inability to use past experiences and expert knowledge to improve cost estimates, hence Bayesian which was predominately built to solve these challenges discussed is therefore properly placed as an appropriate approach to use considering the research gap and the objectives of the study (Garthwaite *et al.* 2006, and Fenton 2015). Moreover, the use of Bayesian to analyse biological effects of oil spill by Linklin *et al.* (2011), Silva & Costa's (2012) work on cost estimation model for Seoul oil projects, and Assaf *et al.* (2011) and Khatibisepehr *at al.* (2013) findings on the improvement made in cost estimation using Bayesian and parametric technique using data from the Japanese Steam industry critically reviewing in section 4.4.1.3 above all justifies the choice of combining Bayesian with ABC. Thus while ABC provides accurate and traceable cost information on the project at hand Ben-Arieh (2000), Niazi *et al.* (2006), Qian & Ben-Arieh (2008), and Yongqian *et al.* (2010); Bayesian techniques can enhance cost estimates by reducing the error levels in ABC when combined which suggests the appropriateness of this choice to help investigate how cost overruns can be reduced in the upstream oil and gas drilling industry.

In addition to the above, the Bayesian method is fundamentally based on probability as discussed earlier and since the inability of current models to accommodate expert experiences into probabilistic form has been identified as one of the flaws in previous cost models, substantiates the adoption of the method. Again, chapters 1 and 2 of the study established the aforementioned deficiencies in the current cost models which is why Bayesian which have these as part of its theoretical components is better placed for this research (David &Baglioni 1988, O'Hagan 1994, Carlin & Thomas 1997, Congdon 2001, O'Hagan & Luce 2003, and Gelman *et al.* 2014). This is because ABC satisfies requirements discussed in sections 3.2.1 (definition and purpose), 3.2.3 (data input), and 3.2.5 (suitability and applicability) whereas Bayesian on the other hand reasonably cover sections 3.2.2 (theoretical underpinning) and 3.2.4 (risk capture and robustness) which makes their integration into a model cogent as it fulfils the relevant requirements a cost model should possess in view of the problem of cost overrun in the oil industry. Again, findings by Shahab & Abdalla (2001), Roy (2003), H'mida *et al.* (2006), and Tammineni *et al.* (2009) revealed that integrating two or more models to from a single model improves cost estimation as the weaknesses in one is complimented with the strengths in the other when integrated. It is in this light that the choice to investigate if integration of Bayesian and ABC models could improve project cost estimation and reduce cost overrun in the offshore deepwater drilling industry is suitable.

Finally, the other models discussed above possess their own strengths and uniqueness and by the adoption of Bayesian and ABC in this study do not in any way suggest that the others are incapable to offer any solutions in addressing the problem of cost overrun. But as it has been thoroughly shown in this chapter (4) and especially in this section 4.7, the integration of Bayesian and ABC benefits the study because of the possibility to generate probabilistic data usable for cost modelling, the need to formulate a suitable and applicable model for the oil industry among many others which others lack in this context (Zhang *et al.* 1996, Niazi *et al.* 2006, Han *et al.* 2009, Yongqian *et al.* 2010, Chou 2011, Chaudry *et al.* 2013, and Fenton 2015).The model results would be better placed than the other methods it directly proffer answers to the gap identified in this study.

4.8 Chapter Summary

This chapter critically reviewed and analysed previous research on cost estimation models for the offshore deepwater drilling industry thus providing a better understanding of the cost estimation practices used in the industry. The types of cost models were discussed under 3 strands namely: quantitative, mixed and qualitative method. More than 9 cost estimation models were analysed based on their strengths and weakness in providing accurate estimations with limited data, precisely capture risk and/or factor probability results of all the cost variables in the offshore deep-water drilling operations into a model and can be suitable and applicable to the systems and operations of the industry. Activity-based costing (ABC) was found to be the most appropriate cost estimation technique to be combined with Bayesian Network approach into a single model for the study. The rationale and benefits of this choice is strongly argued and justified in section 4.7 above. The chapter also highlighted the gap in the literature. The next chapter discusses the current practices of the adopted model technique (Bayesian Network approach). It also provides analysis of the current elicitation process and proposes an improved elicitation process based on Bayesian Network approach for the cost estimation as part of the researcher's contribution to knowledge. Primary data is collected using the elicitation process for analysis of the model formulation and for the validation of the improved process developed.

Chapter Five

BAYESIAN APPROACH CURRENT PRACTICE AND EXPERT ELICITATION PROCESS

5.1 Current practice of Bayesain approach

Bayesian methods have a long history of being used to identify and analyse risks and uncertainties in projects (Kahn *et al.* 1967, and Linstone & Turoff 2002). Specifically, the use of Bayesian probability networks is currently popular in the field of supply chain, project management, process flow, medical diagnosis, system management and many others (Hawkins & Evans 1989, Morgan & Keith 1995, Risbey *et al*. 2001, Morgan et al. 2001, Walker *at al.* 2001, Ramachandran *et al.* 2003, Risbey & Kandlikar 2007). The opportunity to observe and understand each node (variable) and their dependence and overall impact on the entire system or project is lauded as vital to identify, assess and manage risks and uncertainties (Morgan & Henrion 1990, and Kandlikar *et al.* 2007). The Bayesian Network approach successfully reduces the difference between prediction and reality by less than 10% when it was used to make estimations and policy decisions in complex health and environmental issues engraved with high risks (Hawkins & Evans 1989, Walker *at al.* 2001 and Ramachandran *et al.* 2003). Predictions of global climate change were made using Bayesian Networks and proved to be more than 98% accurate by looking at the nodes (variables) and arcs that contribute to the changes in climate (Morgan & Keith 1995, Risbey *et al.* 2001, Morgan *et al.* 2001, and Risbey & Kandlikar 2007). In all these findings, expert knowledge played a key role that is why Bayesian approach is considered a good option to improve cost estimation in the midst of the increasing complexities, risks, and inadequate data on cost factors in the offshore industry (Perminova *et al.* 2008, and Naseri & Barabady 2014)

Industrial practice in the offshore drilling sector portray the use of expert judgement in an informal way but for the purposes of future research it is relevant to make it formal, explicit and documented (Otway *et al.* 1992). Since risks are rooted in perceptions and can be varying from company to company, the only way to handle it is by eliciting responses from experts (Jaafari 2001, Project Management Institute 2000 & 2004). It is important for the offshore deep-water drilling sector to develop a better method since the consequences of cost overruns of drilling projects are detrimental not only to the companies involved but the global current and future energy outlook in general (Poiate *et al.* 2006, Soon 2007, Marzouk *et al.* 2008, Adnan *et al.* 2009, Yang & Wei 2010). Again, Moller *et al.* (2004), and Kreuger *et al*. (2012) demonstrated the usefulness of Bayesian Network concept for expert judgement elicitation to establish relationship between two or more variables even when only one of the variables are known. In support to the above discussions, the next sections are dedicated for the analysis of the current practices of how experience and judgements are used in making project cost estimates; looking at how experts are selected, the acceptable sample size of experts, formulation of questions and the problems with the current practices. Again, the researcher contributes to knowledge by developing a more improved elicitation process for the offshore drilling industry using Bayes Theorem technique.

5.2 Current state of offshore drilling expert elicitation process

The offshore deepwater drilling sector and the oil and gas industry in general still rely on the use of traditional (informal) expert judgements where experts' views are more often implicit, undocumented and not regulated (Otway & von Winterfeldt 1992, Moller *et al.* 2004, and Kreuger *et al*. 2012). For instance, traditional expert judgement processes do not show how problems are analysed, do not have a defined type and source of data, and do not offer any appropriate technique to interpret results (Moller *et al.* 2004). Moller's observation was backed by earlier work of van der Sluijs (2002) who argued that the real problem about the informal expert judgement process is not about a doubt in the results it produces but the difficulty one stands to face in an attempt to either critique the approach or replicate the process since there is no supporting documentation or records kept (van der Sluijs 2002). In contrast to the current practice (informal elicitation), reported cases of the use of formal expert judgements are explicit, documented and adopt a conscious approach to establish a clear assumptions and reasons underlying the judgement process (Bonano *et al.* 1990, and Keeney & von Winterfeldt 1991). Meyer & Booker (1991) argued that traditional approaches to elicitation lack the capability to enhance the analysis of costs and risks, project evaluation, and knowledge acquisition. Hence it was suggested by Kadane & Wolfson (1998), Krauss *et al.* (2004), Ahmad-Nedushan *et al.* (2008), and O'Hagan *et al.* (2012) that expert elicitation should be formalised as an approach because of its ability to interpret scientific evidence and complex solutions at different temporal and spatial scales to develop models, and to provide empirical results with limited data.

In formal expert judgement, there are several stages or steps that help to understand the many ways elicitation can be done (Otway & von Winterfeldt 1992, and O'Hagan *et al.* 2006). The steps in the elicitation process help to mathematically aggregate individually and collectively elicited judgements for the purpose of modelling (O'Hagan *et al.* 2006). Formal judgement elicitation can be done using any of these methods: face-to-face interview, postal or internet-based questionnaire and telephone interview (O-Hagan 1998, and O'Hagan *et al.* 2006). According to Otway & von

Winterfeldt (1992), Moller *et al.* (2004), O'Hagan *et al.* (2006), and Kreuger *et al*. (2012), emphasis must therefore be placed on the fact that the informal way of eliciting experts' opinions is not only outdated but hinders continuity of learning. Turoff *et al.* (1993), Ford & Sterman (1997), and Linstone & Turoff (2002) challenged the use of informal elicitation by arguing that the arbitrary allocation of a percentage of cost project to cover project unknowns based on company practice is flawed and does not offer opportunity to appropriately diagnose the problem of cost overrun. Moreover, findings by O'Hagan *et al*. (2005), Howe (2006), Brabham (2008), Kittur *et al.* (2008), and Jeppesen & Lakhani (2010) showed several cases of consistent inaccuracies in cost estimation of oil and gas projects which suggest the need to find an alternative process of deriving experts' judgements in a more formal way that can be traced and analysed. Meyer & Booker (1991), and Knol *et al.* (2010) suggested that any proposed framework for eliciting responses in the oil and gas industry should consider the nature of the industry, data secrecy and limitations coupled with cost/time constraints. Importantly, the hallmark of every successful elicitation must faithfully represent the opinions of the experts being elicited and not only that but the process should help experts present their thoughts in a more accurate and precise way using probabilistic form (O'Hagan *et al.* 2005).

Most of the reviewed works on elicitation argued for the formalization of elicitation process. Therefore, the researcher agrees with the recommendations of Meyer & Booker (1991), Sterman (1997), Turoff (2002), O'Hagan *et al.* (2005), Howe (2006), Brabham (2008), Kittur *et al.* (2008), Jeppesen & Lakhani (2010), and Knol *et al.* (2010) on the need to formalise elicitation for the offshore drilling sector by developing a robust framework for expert judgement elicitation in view of the above concerns raised.

5.2.1 Sample size for elicictation

There are a number of issues that can affect sample size in qualitative research; nonetheless, the guiding principle that helps to resolve this is the concept of saturation (Creswell 1998, Jette *at al.* 2003, and Mason 2010). Data saturation is the level at which new knowledge, new concepts and experience will not change the analysis away from the majority opinion or discovery (Creswell 1998). The issue about saturation is the ongoing debate on what constitute the adequate number for sample size saturation to be achieved in a study. Hence different authors have suggested what an ideal sample size for a qualitative study should be. Lee *et al.* (2002) argued that studies that either uses more than one method or conduct an in-depth interview require fewer participants as past findings supports quality of results for such studies. Again, Jette *et al.* (2003) suggested that having enough participants with the expertise in the subject under discussion can reduce the number of the sample size. What constitute "fewer" by Lee *et al.* and "enough participant" by Jette *at al.* remain a question as specific numbers were not given. It was Charmaz (2006) who recommended the use of a maximum of 25 participants for smaller qualitative projects whiles Ritchie *et al.* (2003:84) elucidated that qualitative studies should often "lie under" participants. Although these authors gave specific numbers, they did not offer evidence or reasons why a maximum of 25 or below 50 participants should be used. But Green & Thorogood (2004 & 2009) found that nothing new is found when transcribing after 20 participants are interviewed in most qualitative work and as such argued that participant of 20 should be an ideal maximum size when interviewing experts. Mason (2010) confirmed this after reviewing more than 500 PhD thesis and 300 articles and found that on average qualitative researchers' use not more than 30 participants which supports Creswell suggested range of 20 and 30 participants (1998:128).

Just like most techniques that use qualitative approaches, there is no definite answer on what is considered an ideal sample size for expert judgement elicitation (Department of Energy 1984). Formal expert elicitation conducted on the choice of radioactive waste repository in the United States using data from past environmental assessment recommended the use of 500 sample size by selecting 100 experts from each of the five states involved (Department of Energy 1986, and Keeney & von Winterfeldt 1988). The final decision and reasons given for the choice of the site was found to lack relative importance to the cost of the project (Department of Energy 1986). The results from this exercise generated 42 lawsuits from residents living at the five selected sites contesting the reasons and facts that supported the findings. In contrast to the above, a review of five elicitation exercises with a maximum of 50 experts each from 2008 to 2010 helped in making informed decisions. These cases were: Terrorism litigation-hotel bombing scenario, statistical judgements-strengths of association in multiple scatter plots, Toxicology- chemical toxicity, HINI- federal responses to HINI pandemic, and Continuous Quality Improvement-features in health care (Dalal *et al.* 2011). A three round online based approach where participants were made to fill a “truth” question test and answer experience questions as part of the selection process from diverse group of broad experts. Again, using methods such as cluster analysis, data modelling, and analysis of variance/regression individual responses were analysed to derive a statistical aggregate. Results from all five cases received excellent ratings and commendation as each estimation recorded not less than 95% accuracy (Dalal *et al.* 2011).

Because the sample size for a research have an impact on the generalizability of the findings, it was recommended that depending on the availability of the experts and existing constraint a reasonable sample size that is not too large to contain irrelevant data or too small lacking essential details is advisable (Rowe & Wright 1999). Some researchers maintained that depending on the desired sample size for the research problem at hand, the use of online approach to elicit expert opinion is suggested because of its ease to use, low cost factor and its ability to engage respondents at every stage of the process (Linstone 1978, and Rowe & Wright 1999).

Sunstein (2006) argued that since there is no "correct sample size" for research, focus should be on the objectivity, reliability and validity of the aggregate individual responses and so it is important to have less than 5 experts as a sample size that would provide credible responses than 500 full of biases and heuristics. Perminova *et al.* (2008) argued that the quality of an elicitation process is as good as the quality of the process of selection and the guidelines given to protect the sanctity of the results and not the sample size. On the contrary to the position of Sunstein (2006), if formal elicitation process is to be developed the issue about sample size cannot be disregard. Hence since the average project team size for offshore drilling is between 20-50 people across all the stakeholders, Azhar *et al.* (2008), Kaiser (2009), and Powell & Scyoc (2011) suggested that, the sample size of 20 should be the minimum for elicitation process for the oil and gas industry. The suggestion by the authors is consistent to the findings of Linstone (1978), Rowe & Wright (1999), and Dalal *et al.* (2011) on the need for an appropriate sample size and a well-structured question to minimise heuristics and biases as much as possible. This study would therefore use a minimum of 20 participants for the expert judgement elicitation in adherence to recommendations of earlier researchers. The next section discusses the choice of expert selection process.

5.2.2 Expert selection process

The choice and selection of experts (participants with advanced knowledge and experience in the offshore drilling cost estimation) is one of the most crucial tasks in the elicitation process. Otway & von Winterfeldt (1992) argues that the selection of experts for an elicitation exercise must be organized in a way that a balanced viewpoint is represented to avoid the tendency of choosing experts that believe in one ideology, come from the same department etc. which can lead to biases responses. It is, sometimes, problematic to differentiate between experts with novel ideas on the subject matter and others with little understanding (Otway & von Winterfeldt 1992). Especially, when the sample size of the experts is large, recruiting the right calibre of experts becomes fundamental; as failure to do so can affect the validity of the elicitation results (Dalal *et al.* 2011). Beaudrie *et al.* (2011) suggested that for the sake of the soundness and objectivity of the elicitation process, a preselection question must be answered by all potential participants to help choose the right respondents. The preselection questions are aimed to assess the experience and knowledge of the area to be elicited. In agreement with the same principle used for preselection of candidates by recruitment companies for job positions, Dalal *et al.* (2011), and Beaudrie *et al.* (2011) agreed with the recommendation. It was argued by Dalal *et al.* (2011) that there are enough evidences from companies and other reports on how important preselection questions have helped to sift the right participants from a pool of potential respondents to ensure a balanced representation by capping the number of experts the system can take for a particular group of members with same skills, speciality and knowledge.

Dalal *et al.* (2011) added that this requirement can however be overlooked in companies whereby the elicitation involves members of staff. This is because in industry such as the offshore drilling sector, most companies either employ experienced professionals or recruit graduates who usually undergo a mandatory 1-3 years training depending on the policy of the company which appropriately qualifies most workers as potential experts. To make sure a fair chance is given to all both trained and untrained workers, the researcher argues that all potential expert in a chosen scope of study in the industry, should demonstrate their worthiness as experts by answering the preselection questions. Hence, the researcher agrees with Otway & von Winterfeldt (1992), and Beaudrie *et al.* (2011) on the use of preselection questions to test the knowledge and experiences of experts in order to avoiding selecting wrong experts for elicitation.

5.2.3 Choice of issues and questions

Vital in elicitation is the choice of issues raised and questions asked during elicitation. O'Hagan *et al.* (2006) discussed that when wrong issues and questions are presented, it grants access to implicit judgement which is difficult to analyse statistically. Particularly, one consequence of an inappropriate question is its effects on coordination and cohesion of ideas and distortion of thought processes when for example effects rather than root causes of an issue are analysed (Garthwaite *et al.* 2005, and O'Hagan *et al.* 2006). It becomes important to resolve these issues by determining how to formulate the right questions and how to deal with scope changes during elicitation. The researcher suggests that the key to this answer is that no matter how the question is framed or structured there are important things to fulfil which includes: it must deal with the root causes of the problem, it must provoke a refinement in understanding, and finally it must call the experts into action. The researcher's argument follows the recommendations of Dalal *et al.* (2011) and Beaudrie *et al.* (2011) that questions should be designed in such a way for to express themselves in depth i.e. the use of why, how, to what extent etc. are preferable as much detail and interpretation are received. Again, management of companies or heads of departments are normally the organizers of expert judgement and usually have the tendency to ignore issues that may not be in line with company's vision but could adversely affect current or future projects (Otway & von Winterfeldt 1992). Findings by Dalal *et al.* (2011) revealed that most high level management are interested in sanctioning "highly visible" issues which may be less relevant and perhaps has less-tractable problems than given credence to "small issues" that may possess more danger and risk. It is therefore important that due diligence and attention be paid to any issue raised for elicitation so that issues are granted on merit but not based on management views or perceptions which have sometimes be judged to be wrong (Dalal *et al.* 2011, and Beaudrie *et al.* 2011).

5.2.4 Heauristics and Baises

Heuristics can be defined as a "mental rule of thumb" that people hold for all kinds of judgements whereas biases are inclination to a partial perspective of something without considering the merits for other alternative viewpoints (Garthwaite *et al.* 2005). In effect, heuristics can be said to be a "hidden trap" for biases which can make experts adopt intuitive judgement or heuristics when asked to assess probabilities of events (Garthwaite *et al.* 2005). Bias could either be cognitive or motivational; while cognitive bias occurs in the way information is processed, motivational bias on the other hand is caused by the influences personal interest has on people's opinion or judgement on a subject matter (Meyer & Booker 2002, and Virine 2008). Hence biases such as behavioural bias (i.e. how we form our beliefs), perceptual bias (i.e. ways reality is seen), social bias (i.e. how socialization affects judgement), and memory bias (i.e. how information is retained and remembered) all need to be carefully managed to maintain the objectivity of the elicitation results (Weber *et al.* 1988, and Garthwaite *et al.* 2005). Though use of heuristics in general is not necessarily bad but it can lead to systematic biases and errors if decision is heavily dependent it (Meyer & Booker 2001). Hence Meyer & Booker (2001) suggested that it is good to appreciate the approach and strategies experts use in giving opinions in order to evaluate the performance of the exercise.

A common form of error that arises from heuristic is through representation bias (Kahneman & Tversky 1973, and Nisbett *et al.* 1981). Representation bias are of two kinds: horizontal representation bias and vertical representation bias (Zhang 2008). When there is a tendency to classify one thing with its similarities and predict the future of that thing according to its similarities depict horizontal bias. On the other hand, vertical bias is shown when people judge or forecast things based on its own historical records (Zhang 2008). For example, in soliciting for the views of experts on the probabilistic relations between A and B, the probabilities assigned are often done with much emphasis on the degree of similarity between A and B without considering the unconditional probability between them (Kahneman & Tversky 1973). It is a problem because the probability of A occurring may not be depended on B which makes total reliance on representation biased in this case. Hammerton (1975), and Nisbett *et al.* (1981) found this to be true from results obtained when some respondents were asked to determine the probabilities that Mr Q will be “meticulous, introverted, meek and solemn”. The study revealed that Mr Q can be associated singularly to any of the descriptions and also be known with one of the descriptions because of the others. Consequently, in assigning probability for events, experts should consider both the conditional, unconditional and joint probabilities to better offer a more exhaustive results.

There is significant effect of heuristics and biases on elicitation results if they are not managed. It was argued by Garthwaite *et al.* (2005) that allocating a probability to an event based on a similar example that can be remembered during elicitation is permissible as it can offer useful hints in doing a proper probability assessment but judgement by availability can lead to biased probability distribution for the event in question. To overcome this, Perminova *et al.* (2010) suggested that as much as past probabilities can serve as a guide to current or future estimations, the uniqueness of an event or project should not be sacrificed on the basis of similarity as no single project is the same. Furthermore, this is the anchoring and adjustments heuristic used for judgements which helps experts to estimate an unknown quantity by selecting an initial value and then adjusting it to derive the final estimate. This has equally been criticised to have the potential to distract the credibility of elicited results (Perminova *et al.* 2010). Tversky & Kahneman (1974) demonstrated this through an experiment conducted on the percentage of African countries in the United Nations. It was revealed that experts who started with 10% gave a total estimate of 25% as the number of African Countries in the UN while those who started with 65% ended up with a total estimate of 45%. This suggests that there is a higher chance to have a high estimate if one chooses a higher starting value and the opposite is the same.

Otway & von Winterfeldt (1992) admitted that some biases are unchangeable but suggested that unstated assumptions and cognitive frame, motivations, structural and cognitive biases cannot be left unaddressed since these form the basics of any thought process which is core to elicitation. Unstated assumptions and mind-sets are developed from experiences, databases and shared common knowledge from a person's discipline (Otway & von Winterfeldt 1992, and Garthwaite *et al.* 2005). A conscious "awareness campaign" or a course in critical thinking is needed during the training or briefing of the experts before the elicitation to remind them of the importance of their objectivity to the quality of the exercise (Garthwaite *et al.* 2005). Biases and heuristics can occur during elicitation planning, data collection and analysis. It is, therefore, important to put measures to eliminate or minimise them (Kahneman *et al.* 1982). Pannucci & Wilkins (2010) suggested that biases and heuristics can be avoided through proper definition of requirements, making the process accessible and reliable in the selection process. Similar to the above suggestion, as part of the solution to eliminate biases a study design should be structured in such a way to avoid subjective measures (Perminova *et al.* 2008). Aside the above findings on ways to minimise biases, it can be suggested that internal and external validity analysis could be used as well. By internal validation, objectivity of findings can be confirmed and analysed whiles external validity ensures the generalizability of the findings to other sample group or experts. This confirms the findings that subjective expert judgement can be accurate, objective and reliable as long as it is properly elicited (Ayyub 2001, Meyer & Booker 2002, Gilovich *et al.* 2002, and Virine 2008). The next section examines the data requirements for a Bayesian elicitation process.

5.3 Bayesian elicitation data requirement

Just like most other models in statistics, Bayesian techniques can function effectively when certain input data requirements are adhered to (Bernardo 2003, Berger & Bernardo 2009). Before eliciting for data there should be basis or justification for discussions and the problem or subject for the elicitation should be clearly defined and must be understood by the respondents or experts to be elicited. The first requirement for Bayesian elicitation data is the prior probability distribution (Walker *at al.* 2001, Ramachandran *et al.* 2003, and Risbey & Kandlikar 2007). The prior of a variable is the premise on which the probability distribution that would express one's beliefs about this quantity before some evidence is taken into account (Bernardo 2003, and Berger & Bernardo 2009). Thus the prior probability of an uncertain event is normally represented by the unconditional probability that is allocated before any relevant evidence is considered (Ahmad-Nedushan *et al.* 2008, and O'Hagan *et al.* 2012). The prior probability distribution can be derived using several methods which include; a prior determined from past information or experiments, a prior elicited from experienced experts, a prior chosen from some principles given some constraints among many others (Bernardo 2003, Ahmad-Nedushan *et al.* 2008, Berger & Bernardo 2009, and O'Hagan *et al.* 2012).

The second consideration for Bayesian data is the availability of a likelihood function or the prior which explains the distribution of the statistic or event (Mooney 1999, and Merberg & Miller 2008). Usually model variables form the sampling distribution which simplifies and explains the event been considered. It is imperative to identify the relevant variables that are both theoretically and practically reasonable to use for the purposes of analysis (Mooney 1999, and Merberg & Miller 2008). Analysis between individual sample variables and joint probability distribution can better be appreciated if before the model formulation the appropriate sample distribution was chosen. Hence the underlying distribution of the population to be chosen from must be explained and justified as well as the selection of the sample size. To assign accurate probabilities to explain an unknown event using a given prior may not be enough unless the variables on which the probabilities are dependent have been proven to have the greatest impact through critically review and analysis (Mooney 1999, and Merberg & Miller 2008). For instances, it is more appropriate to choose critical cost factors that affect cost overrun rather than using 'any' cost element which has less impact when selecting sample distribution for a particular model. The reason for sampling distribution is to provide conditional probability distributions to an unknown quantity which is why it requires due diligence in its selection. Again, the likelihood function or model evidence as is known in Bayesian is drawn from the variables in the sample chosen for the model formulation.

Another factor to consider in Bayesian data is how the posterior probability is derived. Lee (1997 & 2004) described posterior probability in Bayesian statistics as a random event or an uncertain proposition with a conditional probability that is apportioned after the relevant evidence or background knowledge on the event is known. Thus posterior probability distribution is the probability distribution of an unknown quantity, treated as a random variable, conditional on the evidence obtained from an experiment or survey (Christopher 2006, and Merberg & Miller 2008). These three data points are essential in ensuring that Bayesian model run as required. To gather these expert judgement data discussed through elicitation, question based interview data collection techniques is used in context of this study. The robust data requirement of Bayesian model equally demands robust process for conducting the expert judgement elicitation as it is crucial to ensure accurate and non-biased data is collected to guarantee objective results for the study.

5.4 Review of existing elicitation process

As knowledge and technology expands, industries are faced with new risks and uncertainties which demands efficiency in project execution, service delivery, cost estimations and all the other services needed for successful completion of projects (Meyer & Booker 2011, and Beaudrie *et al.* 2011). This assertion may be true for many industries that are engaged in mega-projects of which the oil and gas industry is at the forefront. According to Kuempel *et al.* (2007), the standard approach to resolve risks and unknowns are through data collection, extrapolation and modelling. While it is refreshing to acknowledge that generation and collection of data can offer relevant information on the risk at hand, it is most times either too difficult to get or costly to produce (Gilovich *et al.* 2002, and Choi *et al.* 2009). Evidence from reviewed literature such as Morgan & Henrion (1990), Regan *et al.* (2002), and Fryer *et al.* (2006) showed lack of a standardized elicitation process for project cost estimation in the oil and gas industry and specifically the offshore drilling sector. One challenge is that in cases where there is data limitation, risk analysis and cost allocation for such is done arbitrarily (Fryer *et al.* 2006, Morgan & Henrion 1990, and Regan *et al.* 2002).

To improve the elicitation results with limited data, Clemen & Reilly (2001) developed a seven step assessment protocol which included:" background, identification and recruitment of experts, motivating experts, structuring and decomposition, probability and assessment training, probability elicitation and verification, and aggregation of experts' probability distributions". Philips (1999) argued that when experts are identified and recruited, a four stage process which involves: introduction and training, motivation, conditioning and encoding should be followed during elicitation. There is an agreed position from the findings of Clemen & Reilly (2001) and Philips (1999); thus each recognised that elicitation yields credible results than arbitrarily assigning values to risk and unknown parameters but whereas Clemen and Reilly's favoured separate elicitation of the experts, Philips opted for group elicitation. Similarly, five-stage elicitation process synonymous to the components described by Clemen and Reilly was transcripted by Shepherd & Kirkwood (1994) and developed by Walls & Quigley (2001) in an attempt to simplify the process. Garthwaite *et al.* (2005) argued that a four-stage elicitation method: set up, elicit distribution summaries, collate a probability distribution and examine the appropriateness of the elicitation. From the above close agreements in methods presented, it can be seen that all the methods overlap and share a common ground. Given the various steps proposed, there is the need to show equivalence or combination of steps that informs the proposed integration.

Table 5-1 Equivalence between Authors on elicitation process

Process	**Reason for combination**	**References**
7-Step process 1. Background 2. Identification and recruitment of experts, 3. Motivating experts, 4. Structuring and decomposition, 5. Probability and assessment training, 6. Probability elicitation and verification, 7. Aggregation of experts' probability distributions		(Clemen & Reilly 2001)
5-Step process 1. Background and preparation of elicitation 2. Expert recruitment 3. Brief and train experts for elicitation 4. Structure the elicitation process 5. Elicitation exercise	Walls & Quigley (2001) argued steps 5-7 of the Clemen and Reilly's process all form part of the elicitation process which do not need to be separated. It was seen more of a repetition than	(Walls & Quigley 2001)

	distinguished steps on their own.	
4-Step process 1. Introduction 2. Training, 3. Motivation, 4. Conditioning and encoding	Philips 4-step process can be traced in both the 7 and 5 process discussed above. Actually, step 1(introduction) of this 4-step process is the same as the step 1 of both Clemen & Reilly and Walls & Quigley process. Similarly step 2 and 3 represent the step 3 of their process while 4 is the same as step 5 of Walls & Quigley and steps 5,6,7 of Clemen & Reilly.	(Philips 1999)
4-Step process 1. Set up **2.** Elicit distribution summaries **3.** Collate a probability distribution **4.** Examine the appropriateness of the elicitation	A critical analysis of the 5 process shows that this 4-process can be integrated. Thus steps 2, 3 and 4 are all elicitation activity which is captured in the 5th step by Walls & Quigley hence this process could be argued to be a 2-step process in context to	(Garthwaite *et al.* 2005)

	this analysis as some of the steps is covered.	

Table 5-1 above shows there is no major difference between the seven, five and four stage processes discussed except that different phrases were used to describe the same process. The table 5-2 gave reasons why it is necessary to combine the overlapping steps from the 4 process to form an integrated elicitation process that incorporate the core theme of all authors. Hence in view of the similarities in the definitions of the processes explained above, the processes suggested by Morgan and Henrion (1990), Shepherd and Kirkwood (1994), Philips (1999), Clemen and Reilly (2001), Walls and Quigley (2001), Regan *et al.* (2002), and Fryer *et al.* (2006) are integrated into five which include: background and preparation, identify and recruit experts, motivating and training experts, structuring and decomposition and the elicitation as represented by figure 5-1 below.

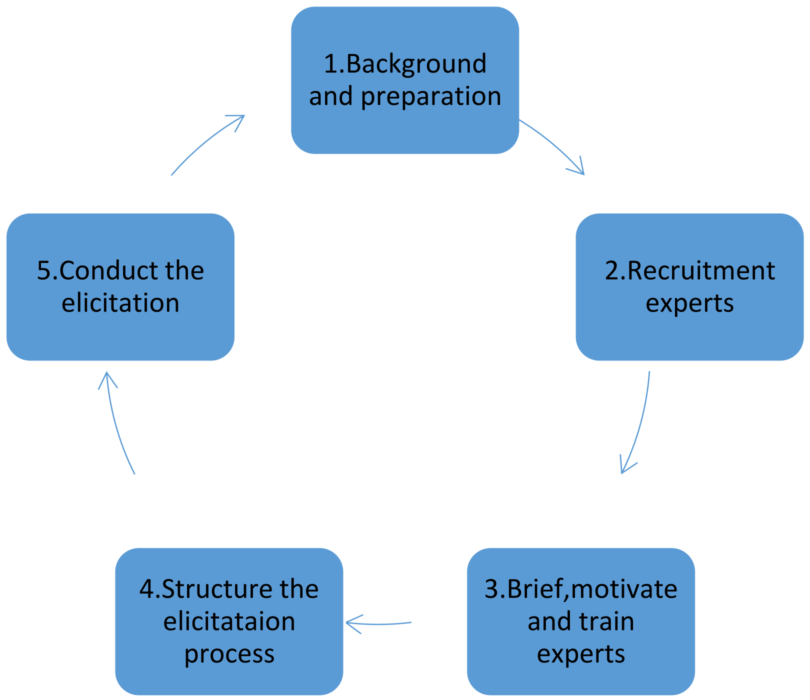


Figure 5-1 Current Elicitation practice (Shepherd & Kirkwood 1994, Walls & Quigley 2001, Clemen & Reilly 2001, Garthwaite *et al.* 2005)

The breakdown of each of the current process is explained below (Shepherd and Kirkwood 1994, Walls and Quigley 2001, and Clemen and Reilly 2001).

Step 1: Background and preparation

- The project owner or person in charge of the elicitation must define the scope and purpose of the elicitation as part of the background and preparation step. This gives direction and shape the elicitation process.

Step 2: Recruit experts

- After the scope and purpose of what is to be elicited is clearly defined, the next step is to recruit the experts for the process. This is normally done using pre-selection questions to test the understanding and knowledge of the experts on the subject matter.

Step 3: Brief, motivate and train experts

- This step involves providing the needed information about the elicitation process.
- Offer training on materials or equipment's to be used if participants are not familiar with them.

Step 4: Structure the elicitation process

- Determine the resource need for the elicitation process e.g. recorder, paper, pens, laptops etc.
- Think about the audience/respondents (experts) and what they need to know about the elicitation process.

- ❖ Determine the question technique (open/closed ended) and the approach for the elicitation i.e. is it going to be based on structured theme/headings or it questions would be randomly asked.
- ❖ Keep questions simple to ensure they are clear and unambiguous and present the same meaning and understanding to all respondents.
- ❖ Determine if there is any missing information and make provision for that
- ❖ Determine how the results/responses from the experts would be analysed

Step 5: Conduct the elicitation

- ❖ Explain how respondents should document the views by providing guidelines for the presentation.

Goulet *et al.* (2009), attempted to elicit statistical distributions from expert in cases where real data is scarce or absent using the above process but found it challenging. This was so because the current process was not inherently built on any statistical theory or framework (Goulet *et al.* 2009*).* Findings by Virine (2009) confirmed the publication of Goulet *et al.* which argued that the most appropriate way to ensure quality of expert judgements during elicitation is to build the process on a consistent and standardized procedures or theory. Hence for the purposes of cost modelling, the current elicitation process lacks the rigor and robustness to deliver on the aim of the study. To address the identified weakness and as one of the contribution of knowledge of this research, an improved elicitation process based on probability based questions has been developed in section 5.5 which has been piloted and used in collecting the data for the main study in section 6.6 in chapter 6 to support Bayesian model formulation. Aside from formulating the process based on probability, credence was given to issues such as; preparation of experts for the interview, conducting of actual interview, comparing expert judgements with results in literature and review and evaluation of expert opinions based on actual data as suggested by Goulet *et al.* (2009), and Virine (2009) to ensure credible elicitation process. Detailed discussion on the improved Bayesian elicitation process developed as a major contribution to knowledge is presented in the next section.

5.5 Improved Bayesian elicitation process

While the current elicitation process discussed in the previous section has been used to make decisions in many industries such as supply chain Walls & Quigley (2001), construction Clemen &Reilly (2001), and Fryer *et al.* (2006), and policy directions Regan *et al.* (2002), its lack of details, depth and rigor raises doubts about its adaptability in oil and gas industry (Garthwaite *et al.* 2005). Hence considering the complex and interrelated activities in the offshore drilling sector, a more detailed elicitation process is required. Therefore, the proposed improved elicitation process makes up for the weaknesses in the works of Clemen & Reilly (2001), Walls & Quigley (2001), and Shepherd & Kirkwood (1994). Based on the review by Garthwaite *et al.* (2005) who criticised the works of Clemen & Reilly (2001) to be too general and vague, the researcher has developed an improve elicitation process that can elicit probabilistic responses for cost estimation based on the weaknesses in the identified in the current cost estimation models analysed in chapter 4. The improved version is tailored to the offshore drilling industry, it is more comprehensive and robust enough to produce a better elicitation results. Figure 5-2 below presents a 12-step flow chart for the elicitation process.

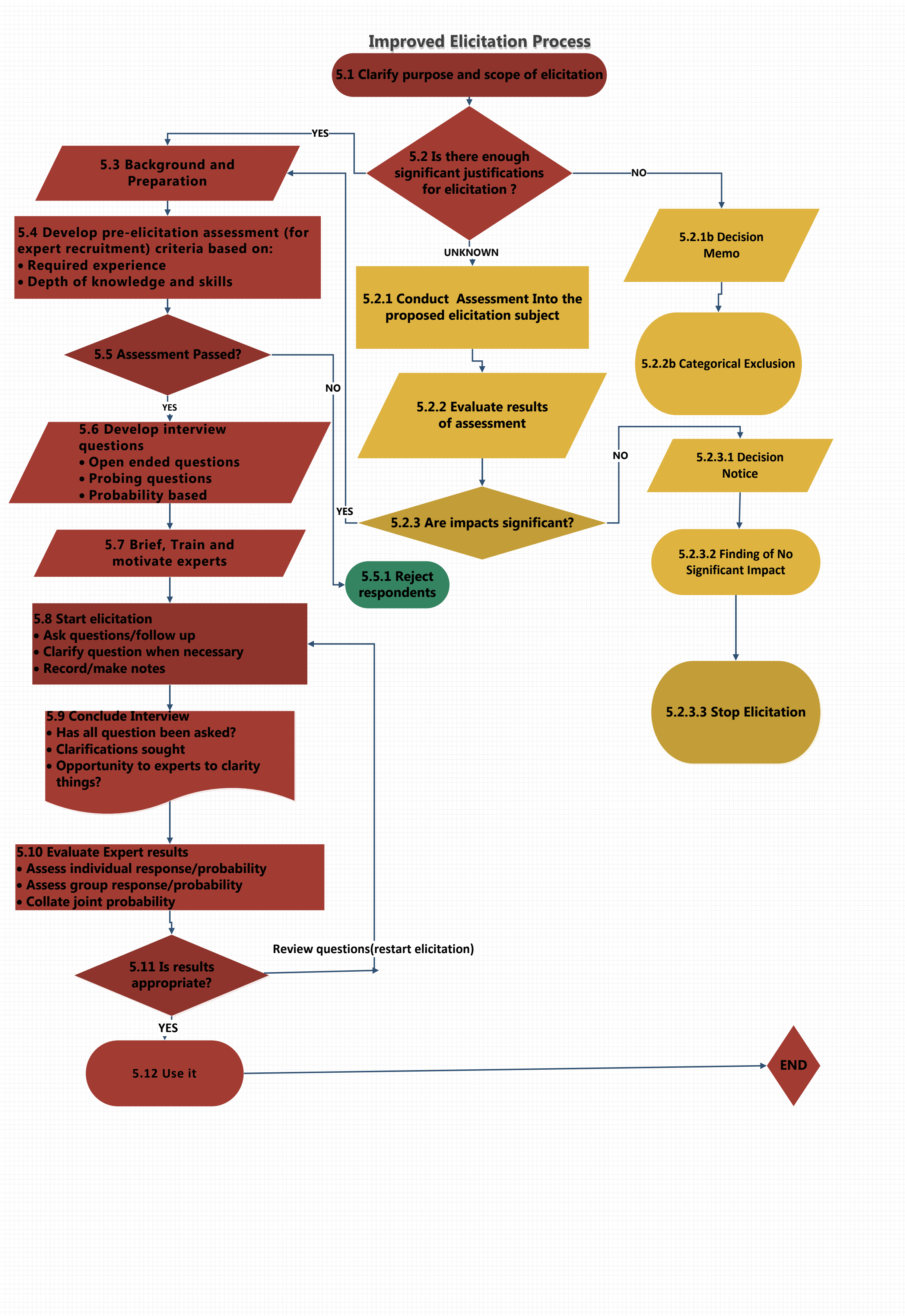


Figure 5-2 Proposed improved elicitation process

To use this new elicitation process, the researcher has prepared a comprehensive guideline that needs to be follow in order to use it. Table 5-2 below gives detailed account of each of the process shown in figure 5-2 above.

Table 5-2 Improved elicitation process guidelines

Process step	**Definition of process**	**Justification of process**
5.1 Clarity of purpose and scope of elicitation	Scope of elicitation is what is to be included as part of the reasons of elicitation whiles purpose defines the aim or what the elicitation seeks to achieve.	Many elicitation exercise fail if the scope and purpose are not defined properly which makes it essential to clearly define these (Cook *et al.* 2005 and Goulet *et al.* 2009). Also is critical to define the purpose and scope before setting any requirement for the elicitation process. Again, it is the general practice that scope is defined prior elicitation to give clarity in terms of magnitude of complexity, risks associated with, and likelihood of success rate.
5.2 Is there enough significant justification for elicitation?	Give explanation, fact or reason why the elicitation should be done on that specific subject	Without the justification, the elicitation may be interpreted unnecessary. Providing The

		significance of Justification helps provided the needed narrative explanation on the idea or reason for elicitation.
5.2.1 If answer to 5.2 is UNKNOWN, go to step 5.2.1 Conduct assessment into the proposed elicitation subject	This helps in deciding the quality and importance of the subject or problem worthy of elicitation	Whenever the justification of an elicitation is unknown, conducting an assessment on the validity of the subject under consideration helps to provide further evidence or facts to in making a decision on what to add or remove from the exercise.
5.2.2 Evaluate results of assessment	After the assessment has been conducted on the unknown elicitation justification, findings should be evaluated.	The relevance of process 5.2.2 is that it helps to ensure that objectives are met, and aid in identifying successes. Also, problems and weakness can be identified and rectified whiles information to aid further development can be uncovered. Again, it presents opportunity to identify expert training needs and offer useful

		guidance for future elicitation
5.2.1b If answer to 5.2 is NO, go to step 5.2.1b Decision memo	If there is no clear justification to discuss any subject or issue in the elicitation, this must be documented and explained	Any decision taken in this elicitation process should be explained and justified.
5.2.2b Categorical exclusion	Following decision on 5.2.1b,	Any subject or issue that lacks justification or significance to the purpose and scope of the elicitation should be excluded
5.2.3 Are impacts significant?	Give explanation, fact or reason why the elicitation should be done on that specific subject	Without the justification, the elicitation may be interpreted unnecessary. Providing The significance of Justification helps provided the needed narrative explanation on the idea or reason for elicitation.
5.2.3.1 If 5.2.3 is NO, go to step 5.2.3.1 Decision Notice	If after assessment has been conducted and there exist not enough justification for elicitation decision present a decision notice as such.	It is important to justify or notify stakeholders of the elicitation why certain issues cannot be undertaken.
5.2.3.2 Finding of No significant impact	Give findings of no significant impact to support the decision notice in 5.2.3.1	Document the reason/s

5.2.3.3 Stop elicitation	Where findings suggest no significant impact of the issue/subject to be discussed such issues should not form part of the elicitation	To avoid wasting time, money and resources only relevant issues should be considered during elicitation
5.3 If answer to steps 5.2 and 5.2.3 is YES, go to step 5.3 Background and preparation	Provide background for the elicitation by: ✓ Clarifying the stakeholder's needs, and the purpose of the elicitation. ✓ Defining the elicitation agenda. ✓ Identifying critical stakeholders who should participate in the workshop. ✓ Arranging logistics and equipment's for the elicitation process. ✓ Deciding what means will be used to document the output of the elicitation.	The importance of this step is based on the fact that a problem well defined helps respondents to prepare adequately and to give meaningful and relevant answers to the questions asked.
5.4 Develop pre-elicitation assessment criteria or questions	A criterion for selection of experts should help to: ✓ Decide who qualifies to be elicited based on the agreed qualification criteria set by the facilitator. ✓ Conduct pre-elicitation interviews or administer pre-	The quality of responses from elicitation is as good as the quality of the respondents recruited (Goulet *et al.* 2009, and Virine 2009). This step 2 of the improved process

	selection questionnaires to the experts. ✓ Select qualified respondents based on the pre-selection interview results	ensures that the respondents with the right skills and experience are recruited and used for the elicitation. To avoid bias in the selection process, this step helps to give fair chance to only those that are qualified to be elicited which adds to the credibility of the final results.
5.5 Assessment passed?	Determine how many of the respondents passed the pre-elicitation criteria check so as to know the sample size for the main elicitation	Only respondents that passed the pre-elicitation questions should be elicited in the main study
5.5.1 If 5.5 is NO, go to step 5.5.1 Reject respondent	If the basic pre-elicitation question is failed, the respondent must be rejected for the main elicitation exercise	Failed respondents are regarded are regarded to not have the adequate experience and knowledge for the subject in question.
5.6 If 5.5 is yes, go to step 5.6 Develop interview questions	✓ For the purposes of modelling questions should be built logically around the problem to be solved. ✓ Network of questions should cover all the activities and factors that affect the problem at hand.	The structure of the elicitation could have an impact on the quality of response. Thus if questions are not logically and chronologically asked it could distort the thought

	✓ Numbers (probabilities) should be used to represent or describe the values or ranges for each opinion or response to help calculate for probabilities.	of respondents which can affect the quality of response they give. For instance, it is more appropriate to ask questions about the causes of event/something before addressing the effects or impacts and not the vice versa.
5.7 Brief, Train and motivate experts	✓ Give relevant information on the issues in advance to prepare the attendees and increase productivity. ✓ Update respondents on current research trend on subject area. ✓ Establish a professional and objective tone for the meeting. ✓ Enforce discipline, structure and ground rules for the meeting. ✓ Introduce the goals and agenda for the meeting. ✓ Manage the meeting and keep the team on track.	Studies have shown that respondents feel relaxed, prepared, and confident about the answers if they are briefed on issues to be discussed, structure of the interview and what is expected of them (Shepherd and Kirkwood 1994, Walls and Quigley 2001, and Garthwaite *et al.* 2005). Which is why this improved process step lay much emphasis on motivating and training of experts before the actual elicitation exercise. The medium of the briefing could be in a form of flyer, document or email explaining the

		agenda and goals of the elicitation and the expected conduct of respondents.
5.8 Start Elicitation	✓ Ask questions that address the root causes of the subject under consideration ✓ Elicit the probability distribution on each variable discussed as appropriate ✓ Ensure all participating expert make their input heard. ✓ Elicit and analyse responses given. ✓ Identify conflicting views and obtain consensus.	The nature of eliciting subjective judgement demand that experts are given the free will to express their thoughts. Therefore, semi-structured approach and open ended questionnaires provide the has been argued to be most appropriate for elicitation exercise (De Vaus 1993, Shepherd and Kirkwood 1994, Ross-McGill *et al.* 2000, Stevinson and Ernst 2000, Bauhofer *et al.* 2001, Burrows *et al.* 2001, Walls &Quigley 2001, Garthwaite *et al.* 2005, Cook *et al.* 2005, Goulet *et al.* 2009, Virine 2009), and Simon 2011).

5.9 Conclude elicitation interview	Give the respondents opportunity to clarify things or make additional comments. Address any questions that the respondents may have.	Relevant issues might have been ignored.
5.10 Evaluate expert results	✓ Collate and analyse joint probabilities and determine their significance (ability to change position of prior knowledge or data). ✓ Check for any inconsistencies in the individual and joint probability and seek clarification	Critically analyse the similarities and differences in opinions and probability of the experts to better put the final results in context. Check results against literature to verify its validity and credibility.
5.11 Is result in 5.10 appropriate?	Check if the results fulfil the scope and purpose for which the elicitation was carried out.	All results must address the purpose for which the elicitation was arranged.
If NO to 5.11 go to 5.8 Review elicitation questions and restart elicitation (go back to step 5.8)	If result is deemed inadequate the elicitation exercise must be rerun with a revised questionnaire from the earlier one.	To better improve results and learning it is good to seek for more information from experts in aspects of the elicitation that affected the final results.
5.12 If YES to 5.11 go to step5.12 Use the results	After a satisfactory joint distribution has been achieved and validated, the results can then be used for modelling, decision making etc.	Apply elicitation results to process, use for modelling or any other areas it may be needed.

5.13 End process	End process	End process

The above improved elicitation processes and guide has been piloted and used to collect the primary data required for the model formulation and the results and discussion in chapters 7 and 8 respectively. This process therefore has been independently verified and validated as workable framework that can help provide critical subjective expert judgements in the oil and gas industry and in many other industries. Hence the above process and guide provided by the researcher are major contribution to knowledge and fulfils the 2nd and 3rd objectivise of the study and the research overall aim. Section 6:6 in the next chapter provides detail analysis of the pilot study and processes used to collect data for the main study.

5.6 Chapter summary

The current use of Bayesian Network approach and expert judgement elicitation in the oil and gas industry was discussed and analysed. Critical issues such as sample size selection, expert selection, choice of questions and heuristics and biases during elicitation were examined and evaluated. To understand the best process required for Bayesian elicitation, data requirement discussions was done which helped to critique the current elicitation process and to identify the gap for improvement. It was evident that the current model in section 5.4 lacked any statistical basis and as such could not help deliver the relevant data required to build the Bayesian model intended for this study. Hence as one of the contributions of this research, an improved elicitation process was developed which has been piloted and used to collect data for the study.

Detailed analysis of the pros and cons of the improved elicitation process is covered in section 6.6 in the next chapter.

Chapter Six

RESEARCH METHODOLOGY

6.1 Introduction to research methods

It has been shown that the reason for poor performance of cost models is due to the inability to capture cost factors such as services, rig, logistics, equipment and materials and administration and cost drivers (politics, delays and depreciation of currency) as discussed in sections 2.3 to 2.3.5.5 and summarised in figure 2.4 in chapter 2 of this thesis. It has been demonstrated in chapter two that to understand and identify the causes of cost overruns is the first step towards finding a solution to the problem. The ability to estimate the impact of cost drivers was found to be very crucial if cost overrun is to be reduced as analysed in section 2.3.5.3 to 2.3.5.5. The evaluation of past cost estimation models against the model requirements for the offshore industry in section 3.2 revealed their limitations to incorporate the identified cost drivers to generate cost models with limited data as the gap in research. Hence the research aim, objectives, and methodology were developed from the inspiration of the gaps identified in the study. These gaps are as a result of the lack of a validated framework that can give accurate estimations with limited data, precisely captured risk, factor probability results of all the cost variables in the offshore deep-water drilling operations into a model and can be suitable and applicable to the systems and operations of the industry.

The methodology discusses the steps used to identify the estimation approach that can help improve the accuracy of prediction of offshore deepwater drilling project cost and reduce cost overruns. To achieve this aim, the improved elicitation process in section 5.5 was used to collect primary data on the contribution of critical cost factors for the model formulation and analysis. Again, secondary data was collected from literature, case studies, and company annual and monthly reports, and published operational and financial reports to adequately fulfil the aim and objectives of this study. Therefore, this chapter identifies the method and techniques used to answer the set-out objectives of the study. Specifically, section 6.2 explains the research philosophy and paradigm while 6.3 defines the epistemology and ontology. Again, the research approach is discussed in section 6.4 whereas data collection and quality of research are discussed in section 6.5 and 6.6 respectively. Finally, the research method and data analysis method adopted are explained in section 6.7 and the chapter summary covered in section 6.8.

6.2 Research philosophy and paradigm

The approach and line of argument of researchers are most often informed by the research philosophies and paradigm they are subscribed to. It is important to discuss this as a study has shown that philosophical perspectives affect the nature of theories and their relevance to research methodology (Gray 2009:15). It is equally rewarding to do so as future researchers can obtain guidance on which philosophy best suits a project. Dewey (1948) evaluated the nature and uses of theory in practice and sought clarification on whether research begins with theory or theory should be as a result of research. This brought about two general paradigm of enquiry in any scientific approach namely inductive discovery ("is a logical process in which multiple premises, all believed true or found true most of the time, are combined to obtain a specific conclusion") and deductive proof ("is a logical process in which a conclusion is based on the concordance of multiple premises that are generally assumed to be true") (Dewey 1948, Cater & Little 2007, and Gray 2009). Whereas deduction begins from a general to a particular situation, induction moves from fragmentary details to a connected view of a situation (Gray 2009:16). Deductive approach is best built for testing hypothesis where the inherent principle is confirmed, revised or rebutted. It suggests that ideas and concepts are abstracts in themselves but underpins the building of theories and hypothesis. Therefore, Cater & Little (2007) reasoned that the significance of deductive approach is much appreciated through empirical observation or experimentation. This is relevant to this study because having a broader view of project successes and failures helps to structure project activities in the offshore drilling operation.

Inductive approach is best suited for data collection which permits the analysis of relationships between variables. It is understandable that though the deductive approach is good in its own right but Gary (2009:19-23) argues that generalization can be constructed only after observation has been made. According to Schmierback (2005), to ensure the reliability of research, the inductive approach becomes essential as it helps to discover binding principles and offer a process to make informed conclusions on the basis of data devoid of any hasty inferences. The use of inductive process cannot be done in absolute isolation without depending on existing theories or ideas in an attempt to respond to a problem. In fact, before an issue is selected for research due diligence is done on what issue is deemed suitable based on existing values and concepts. Inductive approach improves the formulation of research and is no way set out to validate or falsify a theory but use gathered data to establish patterns, consistencies, and meanings (Dewey 1948). Though inductive and deductive processes seem to have a different perspective, one can lead to the formulation of the other (de Wall 2001 and de Jong 2003). In the context of this study, both inductive and deductive approach are relevant as any attempt to develop an improved cost estimation model requires first to review existing concepts and theories before a particular process can be adopted. Hence as deductive approach offers a general picture of the kind of model to address the current challenges in the offshore drilling sector, an inductive approach would provide a step-by-step guide so that there is no relevant to overlook. Notwithstanding the choice of which one to select during a research is discussed in the following section. The section briefly discusses the relationship that exists between theoretical basis and the methodologies used in research.

6.3 Ontology and epistemology

The building of any research is grounded on the ontological and epistemological positions. Though, these are not explicitly stated in research but are rather projected implicitly through the methods and approach adopted by the researcher. Marsh and Furlong (2002:17) maintained that ontology and epistemology are the pivots for research as *"they shape the approach to theory and methods"* applied as they arise from the belief systems of the researchers. Therefore, one cannot choose to take or discard them as and when they see fit because both ontology and epistemology are core to any research (Marsh & Furlong 2002:18, and Hay 2002:61). Ontology is defined as the science or theory of being (Marsh & Furlong 2002:18-19) thus "nature of existences and what constitutes reality" (Gray 2009:19). It probes to know: "if there exists a "real" world that is independent our knowledge of it"?

While ontology encompasses the understanding of *what is*, epistemology attempts to comprehend *what it means to know*. Epistemology offers the philosophical basis for making choices on the kinds of knowledge that are reasonable and acceptable (Crotty 1998, and Gray 2009:19). This is important for several reasons which include: firstly, it helps to clarify research design issues by questioning the type of evidence collected, from where, and how it would be interpreted in a research. Again, understanding of this helps researchers to identify which research design is appropriate and which one is not for a study (Creswell *et al.* 2003). Many ontological and epistemological believers have debated on which one amongst these perspectives is supreme or more important in research. Chai (2002) submitted that epistemology only seeks to challenge the notion and orientation of ontology which is a limitation of truth seeking in research. Gary (2009:20), however, rebutted that it is wrong for anyone to argue for or against any of these stands as understanding or maintaining a particular ontological position at any point in time does not necessarily leads to achieving an epistemological stand that is unitary and holistic. It is suggested that irrespective of whether ontology or epistemology is more important or supreme than the other, the most crucial thing is for researchers to accurately seek the truth whether they hold a realist, objectivist or subjective view.

Ontology and epistemology provide different theoretical perspectives of which the two main ones; positivism and relativism are briefly discussed. Positivism accepts the realism position in ontology and their core argument is that challenges confronting the world are external to any researcher and as such, the only measure for these occurrences is through observation ((Marsh & Furlong 2002:19, de Jong 2003, and Gray 2009:21). They believe the ultimate thing worth knowing and understanding are the general laws and causal effects of events (Marsh & Furlong 2002:19). In essence, positivists argue that reality is available to the senses and scientific observation and empirical inquiry must be the basis of research. Popper (1968), and Bryman (2007) described the arguments for positivism as unfit for modern research dynamics as observation alone may not be good enough for certain types of research and the use of senses can be flawed in chemical, financial and other research copes. Despite the weaknesses discussed, Gray (2009:21) posited that the positivist makes use of quantitative research tools which makes their results objective, generalizable and replicable.

In a sharp contrast, relativism or interpretivism is direct opposite to positivism which argues that it is impossible to make an objective statement about the real world. The ontological stand is in direct opposition to realism because it is believed that the “real” world cannot be independent of the social phenomenon and other happenings in the world (Hollis & Smith 1991). Again, interpretivism challenged the use of observation and senses as the sole means to analysis problems in the world. Rather Crotty (1998:67) argued that interpretation of issues confronting the world at any point in time can be analysed using “culturally derived and historically situated interpretations”. Williams & May (1996) added that the core position of interpretivism rests on the use of the schemas of the mind. Natural and social reality are viewed to be different and hence require different kinds of methods. This suggests that interpretivism is open to using variable methods to resolve problems facing the world (Crotty 1998:68, and Marsh & Furlong 2002). Hence researchers should be flexible enough to shift theoretical if the demands of the research problem beckon. In summary, ontology and epistemology are distinct in themselves and have nothing in common and these can be seen from different research methods which are discussed in the next section.

6.4 Research methods

Generally, research approach can be fixed and flexible (Robson 2002), scientific and naturalistic (Galliers 1992) or quantitative and qualitative methods (Gummesson 1991, and Burns 2000) which are the common approaches used for almost every research. The Quantitative approach is built on beliefs and assumption that data must establish a strong proof of the theory in a research setting (Burn 2000). Qualitative, on the other hand, uses an investigative approach through interviews, surveys, and observation made in the form of words (Robson 2002). Debates have emerged for and against each approach which is evaluated in this discussion. It must be emphasised that no one methodology has the exclusive ability in answering all questions and as such both methods are important when conducting research as the approaches are complementary and are often used together. Fundamentally, quantitative research articulates assumptions that are consistent with the positivists' philosophy (Ayer 1959, Popper 1959, Schrag 1992, and Maxwell & Delaney 2004). In an attempt to provide causal explanations for any event, natural science notion is both employed in establishing the ontology and epistemology and the research method for the study. Again, the primary aim in using quantitative method is not to offer interpretation about events but is to determine a direct and exact causation that are undeniable (Nagel 1986). Typically, quantitative methods are expressed in surveys or statistics (Burns 2000). As it is in the case of positivism, it was argued that the disadvantage in a quantitative method is the fact that data collected cannot offer any clear meaning (Tashakkori & Teddlie 1998). However, this criticism is contestable as the core mandate of this method is to explain causal behaviour and not the meaning of behaviour.

Burns (2000) advocated that the key features of the quantitative method are its operation, replication, and hypothesis testing. Thus operation ensures structured steps are used for measurement, replication ensures the reliability of experiment and data collection whereas a hypothesis is systematically created for the purposes of empirical testing. Contrary to the positivists' theoretical perspectives, qualitative methods are usually favoured by relativists. This directly supports the ontological and epistemological position held by relativists of a world that are constructed socially and all knowledge subject to interpretation. Interviews, questionnaires, focus groups and other qualitative methods are used to gather knowledge and insights into a subject matter. The richness of data collected through this approach cannot be disputed but much concerns have been raised about the generalizability, validity, and reliability (Gavin 1998:172). But while Creswell (2003) recognised these limitations, it was suggested that qualitative researchers do not limit themselves to only “facts” but identify how people construct, interpret and give meanings to events. Burns (2000) contested that allowing researchers and participant’s viewpoints can generate possible biases that can nullify the validity of the research findings. While the argument by Burns may be true, it can be based on the above discussions that the development of this method has evolved and have witnessed many changes which has gradually limit the chances of individual biases when conducting research.

6.4.1 Research methodology selected

Onwuegbuzie & Teddlie (2003) suggested that the ongoing debate about the qualitative versus quantitative paradigm should not prevent a qualitative researcher from using a data collection method associated with quantitative approach and vice versa. Mixed methods research is gradually gaining popularity among researchers as it is believed to offer techniques that are practically applicable. Mixed method is now regarded as a third research paradigm that eliminates or minimises the limitations between qualitative and quantitative methods (Onwuegbuzie & Leech 2004). Works by Brewer & Hunter (1989), Greene *et al.* (1989), Newman & Benz (1998), Reichardt & Rallis (1994), Tashakkori & Teddlie (1998), (2003), Creswell (2003), and Johnson & Christensen (2004) explain the philosophical positions, designs, data analysis, validity strategies among other things. While these writers do not believe mixed method provide perfect research solutions, it is not wrong to admit that it best fits together with the insights between qualitative and quantitative methods. In an evaluation analysis conducted by de Waal (2001), it was defined that mixed method fills the common ground in research philosophies, ontology, and epistemology, theoretical perceptive and in research methods which make it a more balanced approach. Current research questions are most times fully addressed using the mixed research method (de Waal 2001).

In the context of this study, the research questions and objectives can best be answered and achieved using mixed methods. This is because knowledge and understanding of the advantages and disadvantages of quantitative and qualitative research open a way for researchers to combine the two strategies which were described by Johnson ad Turner (2003) as the fundamental principle of mixed research. Again, since the use of mixed methods in a way corroborates the research findings across different approaches, it produces greater confidence and a more definite conclusion (Johnson ad Turner 2003). Also, Onwuegbuzie & Leech (2004) argued that when both qualitative and quantitative data are required for a study, the mixed method offers more understanding and rigour by reducing some of the challenges associated with using singular methods. Above all, the mixed-method approach is a great option to expand and improve the scope and analytical power of this study and also offer enormous versatility in research design.

6.5 Data collection

From the earlier chapters, it can be deduced that this study requires two form of data; primary data elicited from experts, and secondary data from cost figures on past projects extracted from existing literature. There are many techniques for gathering data using the mixed method approach which include the use of questionnaires, surveys, interview, direct observation, literature review, and case study among others for qualitative data (Yin 1989, and Patton 1990) while tests and documentation (Greene & Caracelli 2003) are also used for quantitative. A Semi-structured questionnaire was used in the eliciting primary responses from experts as explained in chapter 5. This was appropriate because a review of past research reports demonstrates that using semi-structured questions to derive qualitative and quantitative data collection stands the best chance to minimise biases from the respondents (Sutton 1997, Robson 2002, and Leech & Onwuegbuzie 2009). Again, in elicitation it is important not to restrict the respondents from sharing their views by asking close ended questions which are why semi-structured type of questions that allow experts to wilfully share their thoughts is preferable as follow up questions can be asked, clarity sought and probing done during interview when necessary which a closed ended type of question cannot guarantee (Creswell 2003, and Leech & Onwuegbuzie 2009).

Moreover, in choosing semi-structured interview for the primary data collection and literature for the secondary data, the strength and weaknesses of the other listed options were examined. Patton (1990), and Robson (2002) argued that surveys are not robust for answering real world problems as they are usually used for causal purposes whereas Leech & Onwuegbuzie (2009) supported that surveys, interviews and sometimes cases study best serve in descriptive studies. Creswell (2003), argued that for primary data collection, interviews and questionnaires (semi-structured) are the best techniques to use. This is because structured questionnaires provide little room for digression which can reduce the quality of data collected in elicitation whereas unstructured question could derail the interview process hence semi-structured which offer a better balance of the two techniques (Creswell 2003, Hair *et al.* 2007, Wilson 2008, and Leech & Onwuegbuzie 2009). Besides, the improved elicitation process developed can best be exploited and tested only by using interview and questionnaire as the data collection approach. Hence the choice of the interview and semi-structured questionnaire used to gather the probability distributions of the cost factors and other qualitative opinions of experts on how cost overrun can be reduced using the improved process developed is appropriate and justified in context to the scope of this study.

On the other, literature review was used to collect data especially in cases where there exist limitations in data for the research area or industry for the purposes of analysis and to compliment any short falls of data collected from the primary study (Greene & Caracelli 2003, and Leech & Onwuegbuzie 2009). The use of literature and published documents as a source of data collection ensure quality and rigor of research as reanalysis of results and findings can be made to check the validity of data (Hair et al. 2007, and Wilson 2008). Hence literature review is opted as one of the data gathering source or process because of the wide range of data it offers (Greene and Caracelli 2003, Hair *et al.* 2007, Wilson 2008, and Leech & Onwuegbuzie 2009). Equally, data is extracted from well-established reports and documents in the quest to find a solution for cost overrun in the offshore drilling operation. It must be emphasized that no data is less valuable than the other whether primary or secondary but it is the quality and the ability to use those data to generate objective and insightful analysis that matters.

6.5.1 Primary data collection

The need for an improved cost model as demonstrated in chapter 4 above places demands on the need for the collection of original data because of the identification of poor data coverage as a weakness in the current models. As explained earlier, experts in the oil and gas industry in Ghana, Nigeria, and Angola were interviewed using a semi structured questionnaire while following the elicitation process developed in this study. Semi- structure questionnaire was appropriate in the context of this study as that has been argued to offer enough freedom to respondents to share their opinion and provide additional insight on issues that were not raised even in the questionnaire but are of importance to the research scope (Louise & White 1994, Creswell 2003, and Simon 2011). Since it combines both structure and unstructured techniques, it gives a good balance to the responses as respondents are not limited to a set of pre-determined answers. To proof the viability of these data gathering techniques and the improved elicitation process, a pilot study was conducted which has been explained in detail below. Ethical approval was sought and granted for both the pilot and the main study evidence of that has been attached in the appendices.

6.5.1.1 **Pilot Studies for the improved expert elicitation process**

To test the feasibility, methods and equipment's, researchers normally employ the use of a pilot study. A pilot study is usually used as "a small scale rehearsal of the larger research design" (Baker 1994:182-183, and Polit *et al.* 2001:467). Pilot study does not necessarily guarantee success in the main study however it has the possibility to greatly enhance the likelihood of it if it is well conducted. Generally, pilot studies are used to check that instructions to respondents are comprehensible and devoid of any ambiguity. It also gives advance warning regarding any weaknesses the proposed study might have such as; the appropriateness of the proposed research protocols and methods, and check if respondents have difficulty in responding to the research questionnaires (De Vaus 1993). Again, it is important to establish before the start of the pilot study how to determine if the outcome of the pilot is better or worse off than the original design. This can be done by setting objectives to serve as a bench mark for the evaluating the performance of the pilot study. Ross-McGill *et al.* (2000), Stevinson & Ernst (2000), Bauhofer *et al.* (2001), and Burrows *et al.* (2001) argued that a clear list of objectives add methodological rigour to a pilot study and decreases the perception bias of the "non-significance" belief many have against pilot studies. Furthermore, the objective becomes a measurement of which the success or otherwise of the pilot study is determined using the final pilot results (Simon 2011).

Generally, the results of a pilot study can bring four possible outcomes which include: (i) *Stop*- main study is not feasible-thus the study results do not answer any of the research objectives or add little or no knowledge value to the main research (De Vaus 1993, Ross-McGill *et al.* 2000, Stevinson & Ernst 2000, Bauhofer *et al.* 2001, Burrows *et al.* 2001, Cook *et al.* 2005, and Simon 2011); (ii) *Continue, but modify research protocol*- thus study is feasible with medications; (ii) *Continue without any modifications, but monitor closely*- i.e. study would achieve intend results with close monitoring; and (iv) *Continue without any modification*-research protocol is feasible as designed (De Vaus 1993, Ross-McGill *et al.* 2000, Stevinson & Ernst 2000, Bauhofer *et al.* 2001, Burrows *et al.* 2001, Cook *et al.* 2005, and Simon 2011). These four criteria for success of a pilot study add rigour to the analysis of the study protocol as any of the four outcomes chosen after the study must be justified and not trivially handled. Again, consideration of ethical issues and approval are important to add validity to the research which this research has achieved and evidence of it has been attached in the appendices. The pilot study runs to test the improved expert elicitation process took into considerations all the poi discussed in this section. The next section gives a detailed account of how the improved expert elicitation process pilot study was done.

6.5.1.2 Excerpts from the Bayesian expert elicitation process pilot study

To ensure the success of the pilot study, a structured approach was adapted which included making sure the problem of the study is clearly defined. The definition of the pilot study in this context was for the researcher to identify a gap between some desired situation and the current situation of the research protocol i.e. the criteria for success or failure. The pilot study is regarded to have been successful if these outcomes are achieved ii) *Continue, but modify research protocol*- thus study is feasible with medications; (ii) *Continue without any modifications, but monitor closely*- i.e. study would achieve intend results with close monitoring; and (iv) *Continue without nay modification*-research protocol is feasible as designed (Burrows *et al.* 2001, Cook *et al.* 2005, and Simon 2011). Following the discussions on the general consensus for success or failure in a pilot study in section 6.5.1.1 above, the researcher considers the pilot study to have still succeeded but the main study should not go ahead if the outcome from the analysis of the results is (i) *Stop*- the main study is not feasible. To achieve any of these successful outcomes, there was the need to organize the pilot study in a way similar to the environment and conditions of the main study as well as using the same criteria for selection of respondents in the main study.

In accordance with the findings in 5.2.1, the sample size of the pilot was 30 postgraduate students (MSC Oil and Gas Management) at Coventry University UK who are made up of workers from service companies, International Oil Companies (IOC) and National Oil Companies (NOC). After administering the preselection questionnaires to the 30 respondents 7 experts who are made up of 1 female and 6 males of which 3 works for international oil companies (IOC), 2 for national oil companies (NOC) and 2 for service companies (SC) made it to the pilot study panel. the demographics of the respondents was necessary as it is anticipated that the experts in the main study would fall under these categories and hence have an idea of the similarities and differences of opinions from each sector would only help better the results and the elicitation exercise. Because the time frame for the cost estimation is from 2005-2015, each of the 7 experts who qualified had to have more than 10years experience in offshore drilling and are familiar with project costing and cost overrun and had worked or are still working in offshore fields in the sub-Sahara region which were the criterion required to qualify as an expert in this context. This was thought to better position them to speak to the issues and scope of the study. Also, it was important to ensure the experience and skill level of the pilot study personnel were typical to what would be found on the field in the main study (Simon 2011). The 7 experts were trained on how the pilot study process and procedure would be and how to use documentations during the process. In order to make use of the pilot results, the 7 experts were asked to bring along any past data financial projection or estimates, documents on projects they would wish to make references to where necessary during the pilot study as has been planned for the main study. It was emphasized clearly that any data referred to by the experts would be for their own use to be able to give credible, objective, and realistic judgments on the what/how/when/ and why offshore projects overrun their cost. Section 5.4.2 below gives a detailed account on the data collection for the pilot study.

6.5.1.3 Data Collection for the Pilot study of the Bayesian expert elicitation process

Bayesian expert elicitation process presents the platform for experts to examine complex problems and provides solutions based on past experiences and skills (Bernardo 2003, Berger & Bernardo 2009, and Simon 2011). It is on this premise the pilot study data were collected. The pilot study was divided into two rounds using the same 7 experts' discussed in the section above. Round involved the pilot participants providing consent before each was interviewed using 5 open-ended semi structured questions which address the research aim and objectives. The demographics of the 7 experts used can be viewed in table 6-1 below.

Table 6-1. Demographics of Experts in Pilot Study Rounds 1 and 2

Code	**Gender**	**Role or Specialty**	**Experience in costing?**	**Work experience**	**Company**	**Work Location**
P001	F	Project Engineer	YES	10-15yrs	IOC	Ghana
P002	M	Cost Estimator	YES	10-15yrs	SC	Gabon
P003	M	Operations Manager	YES	10-15yrs	NOC	Nigeria
P004	M	Cost Engineer	YES	15-20yrs	NOC	Ghana
P005	M	Project Manager	YES	15-20yrs	IOC	Nigeria
P006	M	Project Manager	YES	10-15yrs	IOC	Nigeria
P007	M	Cost Accountant	YES	20yrs+	SC	Nigeria

The questions for round 1 of the main study was used during the interview which can be found below:

1. *What are the causes of offshore deepwater drilling cost overruns?*
2. *How do you evaluate and analyse the critical cost factors in the Sub-Sahara Africa offshore deepwater operations and identify the extent they contribute to cost overrun?*
3. *Using your data give the probabilities of the contributions of the identified cost drivers to cost overrun from 2003 to 2013.*
4. *Identify the limitations of your current cost estimation model used in your operations*
5. *How can offshore drilling cost overrun be reduced/eliminated?*

These questions were derived from the 3 objectives discussed in section 1.5 in chapter 1. It was clear after the round 1 that the respondents did not fully understand what some of the questions meant which made them give generic answers. To analyse the answers, a comparison was done with findings existing in literature and fresh findings that address the research questions. A reflective exercise after the interview with each expert revealed that the questions could best be answered and well followed by both the interviewer and interviewee if themes or headings addressing each objective of the main study is used. Again, the researcher observed during the round 1 that some of the questions and key issues in literature should be explained during the training section to refresh the memory of respondents as some were cautious and reserved in sharing their thoughts because of concerns about the validity and support of those views in literature. Moreover, it became necessary to consider how to manage and control the experts to stick to addressing the questions being asked during the interview as 6 out of the 7 experts tend to talk too much and address issues not discussed. According to Fink & Kosekoff (1985), Lancaster *et al.* (2004), Ruxton & Colegrave (2006), and Simon (2011) facilitators of pilot study should play active role by ensuring respondents stick to the issues been discussed by giving time quota for each question and offer extra time for further issues the respondents would want to talk about after exhausting all the questions for the main study. This was adapted in the round 2 and the training for the experts gave a briefing on current findings in the literature. In round 2 lessons from round 1 were used to modify the arrangement and chronology of the questions which can be seen below:

Face-to-face Semi-structured interview questions 2

The questions being asked below are to help the researcher to understand the causes of cost overrun and to help identify the limitations in existing cost. Again data on the critical cost factors that affect overrun is collected to help in formulating a more robust cost estimation model for the oil and gas industry. Finally, opinions gathered from this questionnaire are used for analysis and discussion on how cost overrun can be reduced/eliminated in this study.

Respondents Opinion on Causes of Cost Overrun

1. *What is your opinion on cost overrun in the offshore deepwater drilling industry in the sub-Saharan Africa?*
2. *What are some of the major causes of cost overrun in the offshore deepwater drilling projects in sub-Saharan Africa?*
3. *Do you consider delays, politics, and depreciation of local currency to be critical cost factors in the offshore deepwater drilling projects in sub-Saharan Africa?*

4. *Relying on your data on past projects, how would you describe the impacts of these 3 Critical factors to cost overrun in your operations?*
5. *Relying on your past project cost estimates on drilling projects, can you please give your opinion on the probability of the contributions of delays, politics and depreciation of local currency from 2003-2015?*

Table 6-2. Probability response sheet

Year	**Probability of Delay**	**Probability of Politics**	**Probability of depreciation of currency**
2003			
2004			
2005			
2006			
2007			
2008			
2009			
2010			
2011			
2013			
2014			
2015			

<u>Respondents Opinion on limitation of existing cost estimation models/methods</u>

1. ***What method/process or model do you use for your project cost estimations?***
2. ***What are the strengths and weaknesses of your current cost model/method?***
3. ***Could you explain if your current model makes use of expert judgement***

4. ***Could you give your opinion on the impact of having a cost model built on expert judgment for offshore deepwater drilling projects?***

Respondents Opinion on solution cost overrun

1. ***What is/are your opinion/s on the integration of models as a solution to reduce cost overrun in the offshore deepwater drilling projects in sub-Saharan Africa?***
2. ***Could explain/discuss ways offshore deepwater drilling projects in sub-Saharan Africa can be reduced or eliminated?***
3. ***Do you consider Bayesian and ABC model to possess better estimation accuracy compared to your current model? Why?***

The results from round 1 and 2 are discussed and analysed in the next section.

6.5.1.4 Analysis of the Bayesian expert elicitation pilot study

To comprehend the results of the pilot study, evaluation of its design, conduct, analysis, and interpretation is discussed. The flow of participants through each stage of the study can be seen through the use of the proposed improved elicitation process in figure 5-2 as explained earlier. The background and preparation involved contacting the module leader for the MSC Oil and Gas Management module at Coventry University to gain access to the participants and booking of a room prior to the day of the study. As explained above, preselection questionnaires were given to potential respondents and the 7 qualified experts were motivated, briefed and trained for the elicitation process. Individual respondents were elicited first through a recorded interview which was an average of 10-15 minutes followed by the group elicitation. Responses and probabilities were collated and were assessed. The improved elicitation process was found to be simple, comprehensive and detailed compared to the current elicitation process shown in figure 5-1.

The 7 experts rated politics, delays, and depreciation of currencies as critical factors that contribute to cost overrun in the sub-Sahara Africa just as the literature has suggested. Other equally important factors mentioned were the *lack of detailed plan, poor resources derivation and allocation, lack of risk management process or procedures, poor team members-lacked of qualified workers, lack of due diligence of supplies and vendors and not having a clear understanding of project scope, objectives have huge impact on cost as every extra cost identified affect the project and obviously increases cost above the budget planned.* The individual probabilities for the 3 critical cost factors for each of the years from 2005 to 2015 can be seen from the pilot study appendix 5. Notwithstanding, a summary of the aggregated averages for each expert on the 3 cost drivers can be seen in table 6-3 below.

Table 6-3. Pilot data breakdown

Reference	Role	Experience	%Politics	%Delays	%Currency
P001	Project Engineer	10-15yrs	25%	35%	40%
P002	Cost Estimator	10-15yrs	35%	35%	30%
P003	Operations Manager	10-15yrs	50%	25%	25%
P004	Cost Engineer	15-20yrs	20%	45%	35%
P005	Project Manager	15-20yrs	45%	35%	20%
P006	Project Manager	10-15yrs	40%	35%	25%
P007	Cost Accountant	20yrs+	55%	25%	20%
Total avg.	**n/a**	**n/a**	**39%**	**34%**	**27%**

Overall, the aggregated average of the experts on the probability politics, delay, and depreciation of currency contributing to overrun was given as 39%, 34%, and 27% respectively as shown in the table above. The averages were calculated by dividing the total number of respondents to the sum of all the individual probabilities for each cost driver which is valid and meaningful according to Niazi *et al.* (2006), Qian & Ben-Arieh (2008), Yongqian *et al.* 2010, and García-Crespo *et al.* (2011). From the table above, it can be suggested that politics is the highest contributing factor of cost overrun in the offshore deepwater drilling industry in the sub region of Africa. A critical look at the individual averages over the years 2005 to 2015 gave a different picture. For example, respondents P001 and P004 from Ghana had contrasting probabilities for each cost factor. Whereas respondents P001 attributed 25% to politics, 35% to delay, and 40% to the deprecation of the cedi as overrun causes, P004 thought delay is the highest threat with 45% probability followed by Cedi depreciation (35%) and politics 20%. Whereas it was not expected to get the same views and opinion from the experts, it is curious to understand however if the difference in opinion can be attribute their roles or responsibilities and a number of years of experience as P004 is a Cost Engineer with 15-20years experience whereas P001 is a Project Engineer with 10-15years. Respondents P003, P005, P006 and P007 all from Nigeria all agreed that politics is the highest contributing factor to cost overrun followed by delays and depreciation of the Naira though each had a distinct probability average as can be seen above. In a nutshell, the pilot study gave a vivid indication of how the main study could play out Pilot 1 revealed the weaknesses in the study protocol which helped to improve Pilot 2 results discussed in this section. It was suggested by Burrows *et al.* (2001), Cook *et al.* (2005), and Simon (2011) that the interpretation of pilot study results should focus on the feasibility taking into account the stated objective and criteria for success of the pilot study. The results from the pilot 2 suggest that the achievement of success criteria 3. *Continue without any modifications, but monitor closely*- i.e. study would achieve intend results with close monitoring. This is because the pilot results have shown that the current study protocol has the capacity to help derive the needed answers to the research objectives and questions.

6.5.2 Primary Data Collected based on the improved expert elicitation process

The semi structured questionnaire 2 discussed in section 6.5.1.3 above was used for the data collection in the main study using the tested improved elicitation process. The experts followed the same process as described in the pilot study. The total respondents for the main study were 33 experts which included 11 from Nigeria, 15 from Ghana and 7 from Angola. The experts were made up of workers of IOC's. NOC's, Service Companies who had a minimum of 10years working experience in the offshore drilling industry for each of the offshore fields in the scope of this study. The tables 6-4, 6-5 below give the demographics of each respondent from the 3 countries to show the dynamism in the experts and for the purposes of analysis determine if at any gender and length of experience help in cost estimation.

Table 6-4. Demographics of Experts in Nigeria elicitation process

Code	**Gender**	**Role or Specialty**	**Experience in costing?**	**Work experience**	**Company**	**Work Location**
N001	M	Operations Manager	YES	10-15yrs	IOC	Nigeria
N002	M	Drilling Cost Estimator	YES	10-15yrs	IOC	Nigeria
N003	M	Project Manager	YES	10-15yrs	NOC	Nigeria
N004	F	Project Engineer	YES	15-20yrs	NOC	Nigeria
N005	M	Cost Manager	YES	15-20yrs	IOC	Nigeria
N006	M	Project Scheduler	YES	10-15yrs	IOC	Nigeria
N007	F	Cost Estimator	YES	10-15yrs	IOC	Nigeria
N008	M	Project Manager	YES	15-20yrs	SC	Nigeria

N009	F	Project Analyst	YES	10-15yrs	IOC	Nigeria
N010	M	Project Manager	YES	+20yrs	SC	Nigeria
N011	M	Cost Engineer	YES	15-20yrs	IOC	Nigeria

In Nigeria, a total of 32 pre-selection questionnaires were issued of which 11 successfully qualified and participated in the elicitation process. From table 6 above, it can be seen that 3 of the respondents were females while the other 8 were males. In terms of their experiences, 6 of the experts had experience between 10-15years which represented 55% of the sample size while 37% (4 experts) had 15-20years experience and only 1 with more than 20years experience which was 8% of the sample size. Again each of the experts is either directly involve or has extensive knowledge on project costing and cost overrun which made them suitable for the exercise. Of the 11 expert's opinion elicited in Nigeria, 7 were workers for IOC's and 2 each for both NOC's and SC's. The probability distributions for each of the experts on the contribution of politics, delays, and the weak local currency has been compiled and document and other opinion shared transcribed for the 10year period (2005-2015) which is captured under appendices 6 of the study. However, the summary of the averages of each respondent has been presented in table 6-5 below for the purposes of analysis.

Table 6-5. Average probability distribution on cost drivers -Nigeria Experts

Reference	Role	Experience	%Politics	%Delays	%Currency
N001	Operations Manager	10-15yrs	40%	30%	30%
N002	Drilling Cost Estimator	10-15yrs	45%	25%	30%
N003	Project Manager	10-15yrs	50%	15%	35%
N004	Project Engineer	15-20yrs	40%	45%	15%
N005	Cost Manager	15-20yrs	45%	20%	35%
N006	Project Scheduler	10-15yrs	60%	20%	20%
N007	Cost Estimator	10-15yrs	40%	30%	30%
N008	Project Manager	15-20yrs	45%	35%	20%
N009	Project Analyst	10-15yrs	40%	35%	25%
N010	Project Manager	+20yrs	55%	25%	20%
N011	Cost Engineer	15-20yrs	50%	30%	20%
Total avg.	**n/a**	**n/a**	**46%**	**28%**	**26%**

It was evident from the elicitation that each expert rated politics to have the most impact on project cost overrun which has 46% probability of contributing to cost overrun. Whiles respondents N006, N010, N003 and N011 gave probabilities of 60%, 55%, 50% and 50% all the other 7 gave probability ranging between 40-45%. Also, the probability of delays and weak local currency contributing to cost overrun had an average of 24% and 25% respectively.

The data collected from Ghana involved 47 potential respondents who went through the pre-selection questionnaires of which 15 qualified for the elicitation. The demographics of the experts is presented in table 6-6 below.

Table 6-6. Demographics of Experts in Ghana elicitation process

Code	Gender	Role or Specialty	Experience in costing?	Work experience	Company	Work Location
G001	M	Finance Manager	YES	15-20yrs	IOC	Ghana
G002	M	Cost Estimator	YES	10-15yrs	IOC	Ghana
G003	M	Cost Scheduler	YES	+20yrs	NOC	Ghana
G004	M	Project Engineer	YES	+20yrs	NOC	Ghana
G005	M	Cost Analyst	YES	15-20yrs	IOC	Ghana
G006	M	Drilling Engineer	YES	10-15yrs	IOC	Ghana
G007	M	Cost Engineer	YES	10-15yrs	IOC	Ghana
G008	M	Budget Analyst	YES	+20yrs	NOC	Ghana
G009	M	Project Analyst	YES	10-15yrs	NOC	Ghana
G010	M	Project Manager	YES	10-15yrs	NOC	Ghana
G011	M	Cost Engineer	YES	15-20yrs	NOC	Ghana

G012	M	Cost Accountant	YES	15-20yrs	NOC	Ghana
G013	M	Project Manager	YES	+20yrs	NOC	Ghana
G014	M	Offshore Engineer	YES	10-15yrs	NOC	Ghana
G015	M	Project Manager	YES	10-15yrs	NOC	Ghana

From the demographics from Ghana, all the respondents were males and 10 of them work for the National Oil Company (NOC) while the remaining 5 work for International Oil Companies (IOC's). The number of the experts with experience between 10-15years was 7 (47%) of the sample size while the others with 15-20years and +20years experience were 4 each. The average probability distributions for the 3 factors for the years 2005-2015 has been summarised below in table 6-7.

Table 6-7. Average probability distribution on cost drivers -Ghana Experts

Reference	Role	Work Experience	%Politics	%Delays	%Currency
G001	Finance Manager	15-20yrs	30	35	35
G002	Cost Estimator	10-15yrs	35	35	40
G003	Cost Scheduler	+20yrs	25	40	35
G004	Project Engineer	+20yrs	30	40	30
G005	Cost Analyst	15-20yrs	45	25	30
G006	Drilling Engineer	10-15yrs	30	25	45
G007	Cost Engineer	10-15yrs	35	30	35
G008	Budget Analyst	+20yrs	40	35	35
G009	Project Analyst	10-15yrs	20	30	50

G010	Project Manager	10-15yrs	20	40	40
G011	Cost Engineer	15-20yrs	40	30	30
G012	Cost Accountant	15-20yrs	35	35	30
G013	Project Manager	+20yrs	25	35	40
G014	Offshore Engineer	10-15yrs	30	30	40
G015	Project Manager	10-15yrs	45	25	30
Total avg.	**n/a**	**n/a**	**32%**	**33%**	**35%**

Generally, the impacts of the 3 factors elicited were closely the same as can be seen from the average probability distributions of the 15 experts. Notwithstanding, individual distributions showed contrasting views on which of the factors had the highest impact on cost overrun. For example, respondents with reference numbers G005, G008, G011 and G015 ranked politics as the highest contributing factor with probability of 45%, 40%, 40% and 45% respectively whereas respondents G002, G006, G009, G013 and G014 rated weak currency above the other two factors with probabilities of 40%, 45%, 50%, 40% and 40% respectively. The only respondent who considered delay as the highest contributing factor in the industry was respondent with reference G004 as illustrated in the table above. The differences in opinions expressed by each respondent could be explained by their experiences on previous projects and lessons learned. Again, the individual probabilities and the transcriptions of the qualitative data can be found in appendices 6 for references.

Finally, 7 out of the 21 potential respondents qualified in Angola after the pre-selection exercise. Similar to the above tables, the demographics and probability distributions for all the 7 experts are represented in tables 6-8 and 6-9 below.

Table 6-8. Demographics of Experts in Angola elicitation process

Code	**Gender**	**Role or Specialty**	**Experience in costing?**	**Work experience**	**Company**	**Work Location**
A001	M	Project Manager	YES	15-20yrs	IOC	Angola
A002	F	Cost Engineer	YES	10-15yrs	IOC	Angola
A003	M	Cost Scheduler	YES	10-15yrs	IOC	Angola
A004	F	Project Engineer	YES	10-15yrs	IOC	Angola
A005	M	Drilling Analyst	YES	15-20yrs	IOC	Angola
A006	F	Drilling Engineer	YES	10-15yrs	IOC	Angola
A007	M	Cost Estimator	YES	10-15yrs	IOC	Angola

Table 6-9. Average probability distribution on cost drivers -Angola Experts

Reference	Role	Work Experience	%Politics	%Delays	%Currency
A001	Project Manager	15-20yrs	35	20	45
A002	Cost Engineer	10-15yrs	40	20	40
A003	Cost Scheduler	10-15yrs	40	25	35
A004	Project Engineer	10-15yrs	30	30	40
A005	Drilling Analyst	15-20yrs	45	25	30
A006	Drilling Engineer	10-15yrs	30	30	40
A007	Cost Estimator	10-15yrs	40	30	40
Total avg.	**n/a**	**n/a**	**37%**	**25%**	**38%**

From table 10, it can be seen that all the respondents work for an IOC and have 2 experts with 15-20years experiences while the experience of the other five is between 10-15years. The table showed that 3 of the experts (A001, A004, and A006) believed weakness of the Kwanza is a major contributing factor to cost overrun while 2 (A003 and A005) opted for politics. Again, 2 of the experts (A002 and A007) rated politics and weakness is the currency to have the same impact. Reasons for the differences and similarities in this prediction are critically analysed and discussed in the results and discussion in chapter 8.

6.5.2.1 Contribution to knowledge of the improved expert elicitation process

The researcher conducted a pilot using the improved expert judgment elicitation process (figure 5-2 above) based on the Bayesian approach for the offshore industry that can generate views of experts in a probabilistic way. This same process was used to successfully collect the primary data for this study which has proven to be a framework that can be used for future elicitations in the oil industry and other industries too. A detailed description and step by step guide on how the process can be followed adequately explained in table 5-2 was applied both in the pilot and main study. Again, the novelty of this study is demonstrated by including risk and how to assess and determine their cost impacts using expert elicitation process.

6.5.3 Secondary data collection

To complete the primary data collected, secondary data on cost overrun causes were gathered from literature and financial information on past projects was extrapolated from company's documents and periodicals. Details of these are explained in sections 6.5.3.1 and 6.5.3.2.

6.5.3.1 Literature review

Literature is not only a repository of knowledge but a review of it becomes a stimulus for thinking (Creswell *et al.* 2011). Burns (2000) explained that the essence of conducting a literature review is not only to summarize previous work and narrow the researchers focus but is also to find the data available and specific methodologies that have been used. This makes the literature review the best way to start the data collection exercise for this study because of the difficulty in gathering data in the oil and gas industry. Aside the politics played with data, oil companies are unwilling to give out data because of strategic and most times commercial reasons. Creswell *et al.* (2011) recommended when there exists difficulty in data gathering, the literature review is a vital sounding board for ideas. Therefore, the historical cost overrun factors were identified through review of past reports as documented in Chapter two of this study. Because data abounds in literature it is important to define what is a “good” and “bad” data and the criteria for acceptance and rejection. A good data in the context of this study is any data that shows consistent accuracy, has a proven record to have achieved a given purpose or solved a given problem, has evidence to have improved an operation, decision making, and planning while bad data lacks them (Hair *et al.* 2007, Wilson 2008, and Leech & Onwuegbuzie 2009). This can be identified by comparing the findings of published works with their aims to determine if the data used was good enough. Therefore, the elicitation data was checked against the listed criteria and cross examined with data from international independent energy agencies such as the IEA, EIA, IHS, Ernest and Young, KPMG and the others to test the quality, accuracy and consistency of the data. Details of the data used for the model development arising from the use of literature review is well reported in section 7.4.

6.5.3.2 Empirical data extrapolation from Secondary Data Sources

The nature of this project necessitated relying on official documents and other reports to fact checked data gathered the field. The criteria for selecting the sources was based on oil operators with the highest stake (highest percentage of oil production right) in the various host country for the study. This was appropriate as each of these oil operators owns more than 60% of offshore drilling projects in the various countries which helps in terms of data collection and project comparison between operators. Reported official documents such as administrative records, periodicals, energy outlook reports etc. from international Oil corporations such as the Tullow Oil in Ghana, ExxonMobil in Angola, and Shell in Nigeria were the primary sources of the offshore drilling cost data. Specifically, offshore deepwater drilling cost data for the period 2005 to 2015 were extracted from the reports of the three companies mentioned using the 10-K structured explained below. The reasons for this time period (2005-2015) were because of the accuracy, validity, reliability, representativeness and for further analysis between the oil operators because commercial drilling started at the Jubilee field in 2003 so it was only fair to start from that year. According to Kleinsasser (2000), Brook *et al.* (2008), and Piekkari *et al.* (2010), for the purposes of trend analysis, sound decision, policy direction, and improving operations, choosing a ten-year data are advisable as it enhances the findings of research. The researcher used Security and Exchange Commission (SEC) 10-K filings which are the global standard for reporting and extraction of operation and financial reports to extract the needed information for this study (Leinemann 2000).

Form 10-K is divided into four parts with each part consists of several different sections of the annual report of the company which is organized as numbered items. An overview of form 10-K's structure with special respect to those items containing balance sheets, operational cost/project expenditure, and other financial information is given in table 6-10 below (Skousen 1991; Leinemann 2000).

Table 6-10: Overview of form 10-K structure

Part I	Items 1 to 4	
Part II	Items 5 to 9	**item8: operational cost/project expenditure
Part III	Items 10 to 13	
Part IV	Item 14	**Financial data schedule

The extraction of the data was focused on items 8 and 14, which contain audited balance sheets, operational cost/project expenditure, and other financial information. Again, the data from the three oil operation companies were crossed checked with independent data from other international energy agencies such as the Energy Information Administration (EIA), International Energy Agency (IEA) and other relevant stakeholder published reports to confirm the accuracy and consistency of the data. In addition to the above sources, data was gathered from the central banks and statistical agencies of Ghana, Nigeria, and Angola on the economic indicators between 2005 and 2015 for the purposes of analysis. Finally, other secondary data sources include journals, articles, books, official reports and internet sources. From section 6.2 to 6.5, the summarised research methods adopted and justified through the discussion for this study is highlighted in table 6-11 below.

Table 6-11: Research methods adopted summary

Item	Adopted Method
Research purpose	Explanatory and Exploratory adopted
Research design	Qualitative and quantitative(mixed)
Data collection techniques used	Interview and questionnaire- (Elicitation on cost overrun factors) Literature review and documents- (financial data on project cost)

6.6 Quality and evaluation of research

There is always the tendency to encounter problems when conducting research which ranges from the quality of the data, the credibility of respondents, and reliability and replicability of the study among other things. It is, therefore, imperative to ensure that in the conduct of research the negative impacts resulting from failure to properly handle any of these issues raised are reduced to the barest minimum. Bryman (2007) explained that the best approach to evaluate and ensure maximum quality of research is by setting criteria. It was emphasised that the criteria set for a research should incorporate the exiting trends underpinning that method. Creswell *et al.* (2003) advised that irrespective of whether qualitative, quantitative or mixed method adopted for a study, evaluation criteria is only to help check if research questions are adequately answered. Owing to the explanation given in this section and in context to the scope of this study, evaluation of the research method is discussed from three selected areas: expert opinion selection; reliability and replicability; and triangulation.

6.6.1 Expert opinion

As reported in the works of Dalal *et al.* (2011), the choice of experts was wide enough to include people with the relevant knowledge in the subject area and narrow enough to eliminate novices. Experts chosen for the study had adequate knowledge of the happenings and trends in the area under consideration. Out of the 33 experts that participated in the elicitation process, the minimum average experience for each was more than 10years. Again, the scope of the study was covered as Nigeria, Ghana and Angola were duly represented.

6.6.2 Reliability and replicability and ethics

Ethical consideration for the study was met as it was conducted under the strict ethical standards stipulated by the University of Warwick for Ph.D. research thesis in the United Kingdom (Merriam 2009). An ethical approval letter is attached as part of the appendices. Hence this thesis strictly adhered to the globally accepted ethical standard, practices, and principles. This study strived to achieve reliability and replicability of the data collected. In view of that, peer reviewed journals and audited company reports and periodicals were used for this study to minimise bias in data collection and ensure reliability. Equally independent energy agencies report on offshore drilling cost projections for oil producing regions and countries were compared to validate the accuracy of figures published by the oil operators. In all the comparison done, there were no major variations in the cost estimates projected by the independent energy agencies compared with the oil operators as the cost of drilling an offshore well. Therefore, the results of this study can be produced by the same researcher in another time or anybody else using the same data (McNeill 1990:14, and Saunders *et al.* 2007). In summary, the study fulfilled all the appropriate legislative and morally accepted conducts in the United Kingdom and maintained the standards that commensurate with professional and academic integrity.

6.6.3 Triangulation

Triangulation is a powerful technique that helps to validate research data by employing cross verification from two or more sources (Robson 2002, Creswell *et al.* 2003, and Bryman 2007). The validity and credibility of the data gathered in this research are strengthened on the basis that the data (opinions) were cross examined from three data sources which included oil operator's reports, international energy agencies reports, the government of host countries reports and data from the reviewed literature. As discussed in section 4.5.2 above, examination of the quality, consistency, and reliability of the data from the three sources minimises biases and enhances the objectivity of the data (Robson 2002, Creswell *et al.* 2003, and Bryman 2007). Multiple methods to gather data, such as documents and data from literature at different times and in different places was used in conducting this primary research which also ensures triangulation. Robson (2002) posited that the use of multiple sources enhances the rigour of research. Equally, Bryman (2007) described triangulation as an approach that enhances the confidence and accuracy of research findings. Therefore, the adoption of the mixed method does not only fulfil the requirements for triangulation but also ensure the ensuing benefits from it are achieved in this study.

6.7 Data analysis, verification, and validation

Verification of models answers the question "Did I build the model right?" whereas validation answers the question "Did I build the right model?" (Pace 2004). In other words, by verifying and validating a model involves comparing the elements of the model system with the description of what the requirements and capabilities of the model were to be. Verification is an iterative process that ensures the formulation of the model is internally complete, consistent, and correct enough to support the next phase (Pace 2004). The validation phase compares model performance with the corresponding standard to determine whether the differences are acceptable given the intended use of the model (Robson 2002, Creswell *et al.* 2003, Pace 2004, and Bryman 2007). Therefore, the cost model development in this study was validated and verified using these validation steps.

- ✓ Firstly, the model assumption which explains the conditions in which the model would work is one of the steps employed to test and prove the model's credibility.
- ✓ Secondly, the limitations or exceptions which explain why the model cannot work in certain conditions are equally explained and justified as part of the validation plan.
- ✓ Thirdly, sensitivity checks are done on the model and the variables to ascertain if there could be a major change to the results of the model due to a change in any of the variables used.
- ✓ Finally, input vs output results and variations of the model are compared with other models to prove its credibility and fitness.

Again, the data was analysed both qualitatively and quantitatively. The qualitative data elicited using Bayes Theorem probability were assigned values for each opinion and the totals aggregated. Moreover, descriptive statistics such as frequency tables, percentages, and graphs, were used to describe trends and patterns of cost overruns in the offshore drilling industry. Equally, Microsoft excel was found useful for some part of the analysis and was accordingly employed. The model developed was validated using past offshore deepwater drilling cost data for the sub-Sahara Africa region from 2003-2013. In conclusion, figure 4-7 below shows the research methodology process employed to understand the research problem and its context, the current industrial practice and the cost estimation model development process.

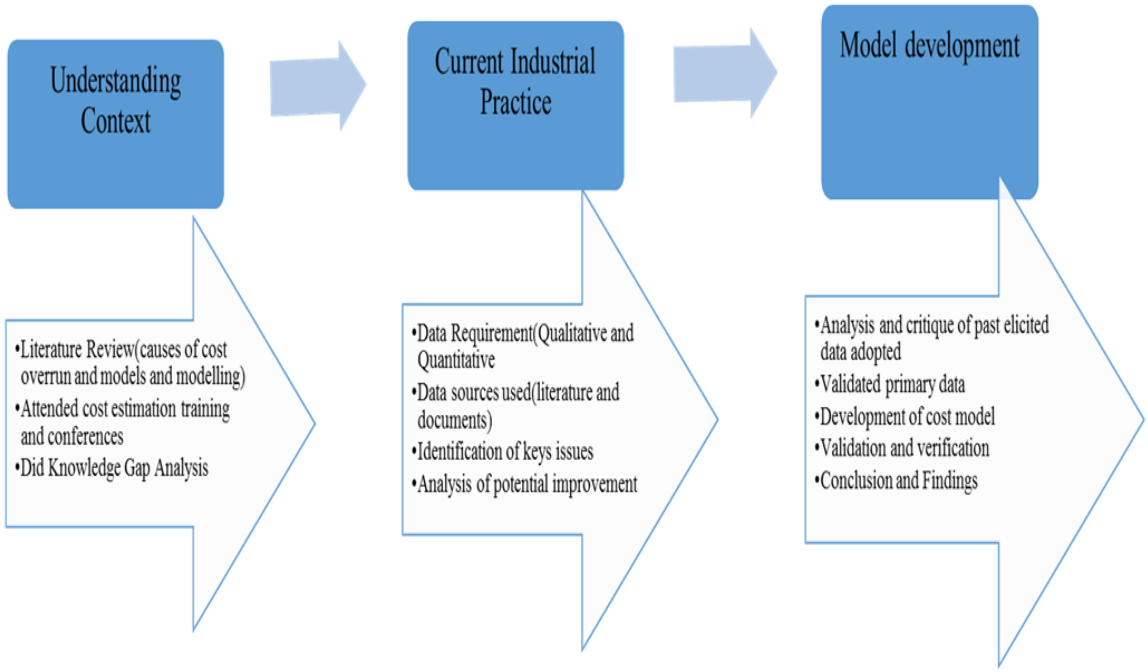


Figure 6-1: Research Methodology process

Figure 6-1 summarises how the researcher demonstrated undertanding of the research context and knowledge gap. It also highlights the current industrial practice by evaluating the current cost models and identifying the required technique and data to reduce cost overrun. The third stage of the diagram projects the model development, analysis and conclusion are captured in the next four chapters. Hence, the input of this diagram is a reflection of the key milestone achieved in the first four chapters and a projection of what the next four chapters present.

6.8 Chapter summary

The methodology that has guided the conduct of this research was discussed in the chapter to achieve the aim, objectives, and scope of the study. It was revealed from section 6.2 that this research falls between the inductive and deductive philosophies as attributes of each was employed. Equally, the ontological and epistemological position informed the choice of pragmatism as a theoretical perspective within which this study is best suited. Correspondingly mixed method approach and convergence design were used for data collection and analysis of the study. More importantly, the quality of the research was critically scrutinized by discussing measures taken to ensure reliability, validation, and replicability of the work. Ethical consideration was strictly adhered to in accordance with the standard provided by the University of Warwick in the conduct of research degrees Ph.D. level. In reference to section 6.6.1 in this chapter, a more in-depth discussion on current industrial practice and proposed improvements (contribution to knowledge) of expert judgment elicitation process are discussed in the next chapter.

Chapter Seven

COST ESTIMATION MODEL FORMULATION AND VALIDATION

7.1 Introduction

It has become increasingly difficult to find an appropriate cost estimation method that is able to predict project time and cost in the oil and gas industry hence the persistent cases of cost overrun in the industry for decades as discussed in sections 2.3 and 3.3. Despite the advancements made in project management in most industries, many projects still face the problem of schedule overrun and project cost overrun (Clark 1985, Ostwald 1991, and Roy & Kerr 2003). In many cases, the problem of cost overrun is due to delays in logistics, decision making and execution (Poiate *et al.* 2006, Yang & Wei 2010, and Powell & Scyoc 2011). There are many factors that contribute to cost overrun in the offshore drilling operation. According to The World Bank (2015), Trading Economics (2015) and other evidence from literatures reviewed (in chapter two) showed that aside delays, political influence and local currency depreciation of the host country against the US dollar are the critical factors that contribute to cost overruns in the offshore deepwater drilling industry in Sub-Sahara Africa. Across many industries, the need for a more improved cost estimation technique to reduce cost overrun has been supported (Jensen 1993, Matson 1994, Qu-Yang & Lin 1997, Lin & Chang 2002, Daniel *et al.* 2011, and Wang & Sun 2012). To achieve the main aim of this study as stated in section 1.5 of chapter 1, this chapter reports on the formulation of Bayesian Networks model that has the ability to both determine the cost impact of the critical factors on drilling projects and predict the cost of offshore drilling projects using data on Ghana, Nigeria, and Angola.

7.2 Proposed approach

Since the factors that contribute to cost overrun are multi-tiered and complex with each variable having its own demands and constraints, Bayesian Network approach is proposed as the most appropriate means to study the effects of each variable and how they can be integrated into a cost estimation model. Table 7-1 below explains the nomenclatures used for the model formulation.

Table 7-1: Nomenclature

X	Probability function on the subsets of S, in probability space (S, P)
x	Distinct elements in the sample space
S	Sample space
P	Joint probability distribution of the random variables in the set X
(S, P)	Probability space
Par(x)	Parents of node x in S
P(B)	Prior or marginal probability of B
P(A)	Prior or marginal probability of A, and does not take into account any information about B
$P(B^c)$	Prior or marginal probability of not B
P(B|A)	Conditional probability of B given A
$P(B^c/A^c)$	Conditional probability of not B given not A

7.2.1 Bayesian Network

The Bayesian model is developed by following the Marr's three levels of model formulation Marr (1982:24), Marr *et al.* (2004), and Mitchell (2009) which are:

1. **Level one: Computation**

This explains what the model does and the logic behind it. Hence by analysing the goal of the proposed model, the appropriateness of the computation logic must be understood in order to fulfil that research goal. This is because it would be erroneous or inappropriate to adopt Bayesian technique in the model building if the proposed study is not partially or fully based on statistics (Mitchell 2009).

2. **Level two: Representation and algorithm**

Representation level ensures that the input and output data are clarified and the output transformational algorithm defined. According to Marr *et al.* (2004), the logic behind the computation informs the type and kind of input acceptable for modelling. For instance, Bayesian modelling require prior and posterior data which are all probability based and hence any data without this characteristic could be regarded as unfit to use in this context. Again how the model is computed is explained at this level.

3. **Level three: Implementation**

Implementation level emphasizes how the algorithm can be used and realised in real world situations.

These three levels are necessary to be followed and understood before the developed model can properly be understood (Marr 1982:24, and Marr *et al.* 2004). The model is built with the understanding that the model variables have been verified to satisfy the two basic assumptions for the Bayesian network. These are:

- ✓ The existence of causal relationship between variables
- ✓ The existence of conditional independence among the variables in order to simplify joint distributions

It is on these assumptions that Bayesian approach is used to provide probabilistic inferences by calculating the conditional probabilities of events from known probabilities using the Bayes rule or theorem. Using Bayes theorem as the foundation for the model formulation, *if A and B are two given events, such that P(A) ≠0 and P(B) ≠ 0* it implies that

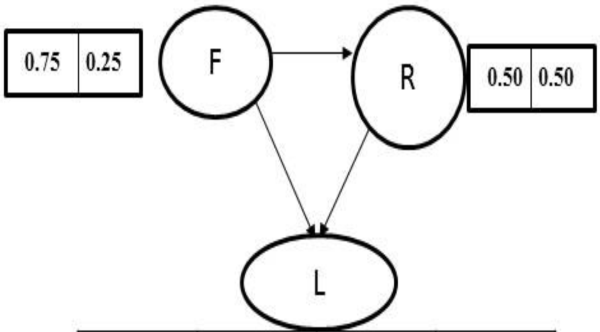
$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \qquad \text{equation (6.1)}$$

Equation (6.1) therefore suggests that, given U mutually exclusive and independent events $A_1, A_2, \cdot\cdot\cdot, A_U$ and B, such that $P(A_i) \neq 0$ and P (B) ≠0. Hence for each i=1, 2…and U, it can be expressed that

$$P(Ai|B) = \frac{P(B|Ai)P(Ai)}{P(B|A_1)P(A_1) + P(B|A_2)P(A_2) + \cdot\cdot\cdot + P(B|A_U)P(A_U)} \qquad \text{equation (6.2)}$$

Applying the principle of Bayes rule, probabilities of events can be computed with the known data (prior knowledge). Thus because B is the known parameter (prior), it provides experts with the needed data to determine the value of Ai (posterior) using equation (6.2)

Example 1: For instance, if event inflation (represented by F) is the cause of increase in prices of two other events rig rates (represented by R) and cost of logistics (represented by L) while rig rates (R) also influences the price of logistics (L), the extent of impact each of these variables have on one another can be assessed using conditional probability. This is done by calculating the associated conditional probability of each node using Bayes theorem to find the conditional probability such as of F given L which is P(F/L). The Bayesian Network in figure 7-1 below show the results of the three random variables using equation (6.2).



F='yes'	R='yes'	0.99	0.01
F='yes'	R='no'	0.90	0.10
F='no'	R='yes'	0.80	0.20
F='no'	R='no'	.00	1.00

Figure 7-1: A Bayesian Network on cost of Inflation on Drilling

Figure 7-1 states that P(F)=0.75 which indicate that 0.25 of F is explained or defined by other factors. Also P(R/F)=0.50 suggests 50% of rig rates is as a result of inflation and the other 50% is informed by other related rig activities. Again, since inflation (F) and rig rates (R) contribute to the price of logistics (L), it is important to understand the extent of the impact of F and R on L which has been given in the table under L in figure 7-1. The probability of L given F and R P(L/F, R)=0.99 which means the price of logistics is 99% determined by inflation (F) and rig rate (R). The result from this example demonstrates that inflation causes the price of rigs to rise whereas the inflation and prices of rig jointly influence the cost of logistics. Again, it can be seen from the figure that when there is no influence from rig rate (i.e. when R is "no"), the cost of logistics is 90% defined by inflation whereas it is 80% defined by rig rate if there is no inflation influence (i.e. when F is "no").

Using equation (6.2) and the information in the probability table in figure 6-1 above, the P(L,F)/P(L) can be expressed below:

$$P(F|L) = \frac{P(L,F)}{P(L)} = \frac{P(L|F)P(F) + P(F/L)\,P(L)}{P(L|F)P(F) + P(F|L)P(L) + P(L|F_U)P(F_U) + 0}$$

From the figure 6-1, the P(L|F)=0.9, P(F)=0.75, P(F/L)=0.01, P(L)=0.2, $P(L|F_U)=0.8$ and the $P(F_U)=0.25$.

Inserting the above probabilities into equation (6.2) equals

$$P(F|L) = \frac{P(L,F)}{P(L)} = \frac{(0.9)(0.75) + (0.01)(0.2)}{(0.9)(.75) + (0.01)(0.2) + (0.8)(0.25) + 0}$$

$$P(F/L) = \frac{(0.675) + (0.004)}{(0.675) + (0.004) + (0.2) + 0}$$

In summary $P(F/L) = \frac{0.679}{0.879} = 0.7679$

Therefore P(F/L)= 76.79 which suggest that there is 76.79% likelihood that F occurred given L.

Results from example 1 again show that Bayes rule or theorem can be used to compute for unknown probabilities from some known variables. Despite the ability of the Bayesian theorem to compute for the unknown, it is limited to relatively simple problems (Jensen 2001). Therefore, in developing an appropriate Bayesian Network model, the first two equations (6.1) and (6.2) are further developed into a probabilistic graphical model that represent variables and their independent probabilities. The Bayesian Network graphical structure has the ability to establish a probabilistic relationship between variables both dependent and independent (Jensen 2001). For instance, given S directed acyclic graph (DAG), the nodes and arcs represents variables and conditional independence between variables respectively. For the probability space (S, P), the probability distribution P can be derived using the product of all the conditional distributions of the nodes (variables) (Heckerman 1995). Because node (variable) is conditionally independent of each other in any given parent, it implies that drilling cost estimates can be made by relying on knowledge of known variables which fulfils the Markov assumption which states that "knowledge of current state solidifies past and future data independent". Therefore, the joint probability distribution of the directed acyclic graph of the N variables is computed as follows:

$$\mathrm{P}(X_1, \ldots, X_n) = \prod_{i=1}^{n} \mathrm{P}(X_i \mid \mathrm{parents}(X_i)) \qquad \text{equation (6.3)}$$

Where Par (Xi) represent the parent node i and X ={x_1, x_2 ……x_N}. From the graphical model, probabilistic statements can be made using the product rule of probability. Using the three offshore drilling critical factors such as politics (A), delays (B), and poor currency performance against the dollar (C) for the purposes of the model formulation, their joint probability can be expressed in the form below.

$$P(A,B,C)=[P(A/C,B)P(C,B)]*[P(B/A,C)P(A,C)]*[P(C/A,B)P(A,B)] \quad \text{equation (6.4)}$$

Breaking down equation (6.4) further, a new equation (6.5) can be derived which is valid for any choice of the joint probability distribution.

$$P(A,B,C) = [P(A/B,C)P(C/B)P(B)]*[P(B/C,A)P(A/C)P(C)]*[P(C/A,B)\,P(B/A)P(A)] \quad \text{equation (6.5)}$$

Example 2: Given the Bayesian network in figure 7-2 below, the joint probabilities of the variables can be calculated using equation (6.5).

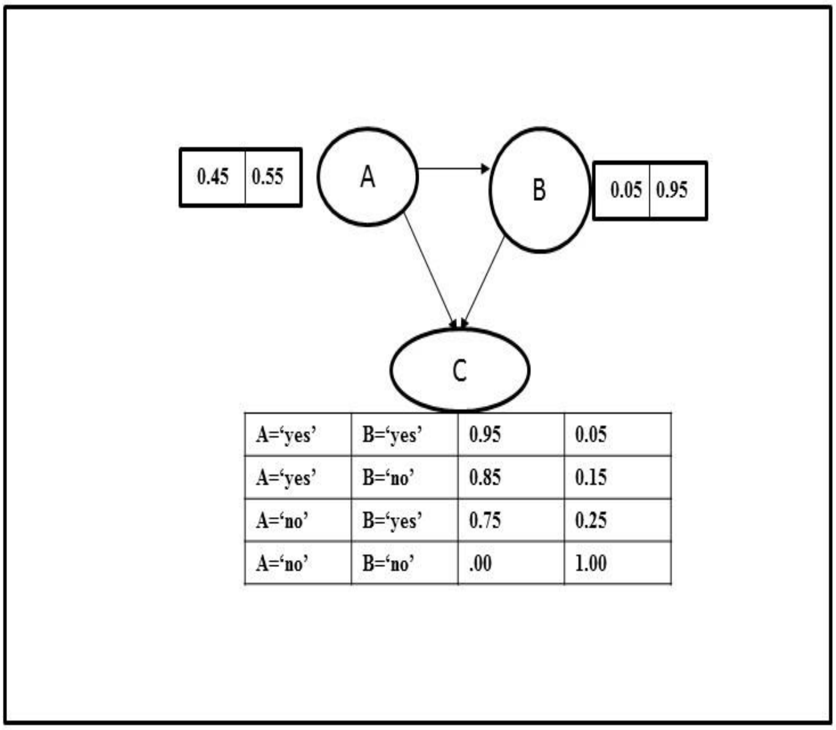


Figure 7-2: Bayesian network with conditional independent probabilities

In figure 7-2 above variable A has a probability of 0.45 which suggests that 0.55 of that variable is explained by other factors. Similarly, variable B has a probability of 0.05 dependent on the occurrence of variable A whereas .95 of the variable is defined by other factors. Again, C has different probabilities depending on whether its probability is influence by either A, B or both. From the figure 7-2 in example 2 above, to compute the joint probabilities of variables A, B, and C a DAG showing their conditional probabilities can be seen in figure 6-3 below. Using equation (6.5) the conditional (dependent) and independent probabilities of each variable (A, B, C) were calculated as shown in the figure 6-2 above to give the DAG.

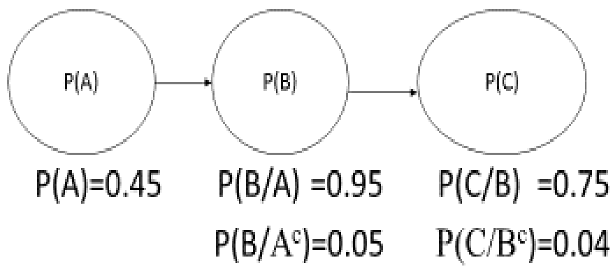


Figure 7-3: Random variables with corresponding conditional probabilities

From the above figure 7-3, the probability of A only (independent) is P(A)=0.45, P(B/A) =0.95 as seen from figure 6-2 represent the probability of B given that the probability of A is known. This suggests that 95% of variable B is partly or fully explained by variable A and similar explanation goes for P(C/B) =0.75 as given in figure 6-2 above. $P(B/A^c)=0.05$ is the probability of B not influenced by A which is seen in figure 6-2. $P(C/B^c)$ is calculated by eliminating the effects of variable B but effects of variable A has to be added to the independent probability of C i.e. (0.85*0.05=0.0425) from the table in figure 6-2.

The prior probabilities of the variables can be calculated using equation (6.1)

$$P(B)=P(B/A)\,P(A) + P(B/A^c)\,P(A^c)= (0.95)(0.45)+(0.05)(0.55)=0.46$$

$$P(C)=P(C/B)P(B) + P(C/B^c)P(B^c)= (0.75)(0.90)+(0.04)(0.11)=0.68$$

The conditional probabilities of the three variables can be summarised below.

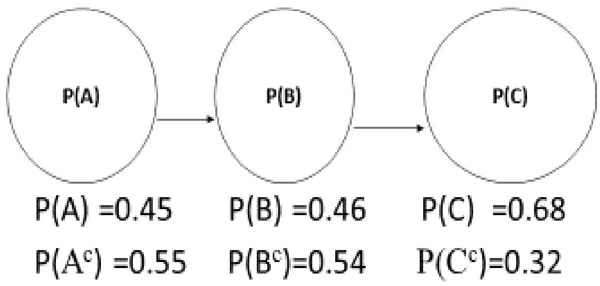


Figure 7-4: Bayesian Network showing probabilities of variables in the network.

The results in figure 7-4 can be used to analyse the performance and changes in the network. Because the variables are interdependent, any change in the probability of a variable affects the overall system performance or results. For instance, a change in the probability of A from 0.45 to 0.7 will change B from 0.46 to 0.49 and C from 0.68 to 0.69 because of the direct effect A has on B and C. Again, equation (6.5) can be used to compute for the independent probabilities of variables in a network. Hence in relation to this research aim, the impact of the drilling critical cost factors on final drilling project cost can be determined from cost overrun historical data through their independent probabilities using equation (6.5). The validity of the model is tested with empirical data in section 6.3 of this thesis.

In synchronising the formulated model to the proposed improved elicitation process in section 5.5 of chapter 5, the acceptable joint probability percentage for the offshore industry can be summarised from equation (6.5) by using the Markov formula below.

$$Rs = \prod_{i=1}^{N} Pi \qquad \text{equation (6.6)}$$

Where Pi is the joint probability of the random variables in network or system and N the sample size (total number of variables). The Bayesian Impact Value (BIV) which examines the change in the reliability of the network or model can be derived from equation (6.5) and (6.6). Due to the huge amount of investments involved in offshore drilling, it is important to set a benchmark for an acceptable joint probability during elicitation in agreement to the developed elicitation process in chapter 5. Based on the primary data collected on the cost variables and using equation (6.5), the Bayesian Impact Value is the final result of equation (6.5) where:

If the BIV <0.2 repeat step 4 to 7 as demonstrated in section 5.5

If the BIV ≥ 0.2 no change as results meets the bench mark

Because the accuracy of cost estimation using this model is sensitive to the joint probabilities used it is important to use the BIV to check the reliability of the elicited responses. This is done by comparing the final joint probability results from equation (6.5) with the minimum BIV of 0.2. This is important because as mentioned in chapter 2 any of the cost drivers have a minimum overrun of approximately 40%, hence it is only logical to improve the accuracy of the individual cost variables if the total cost overrun of a project is to be minimised. The relevance and validity of the Bayesian Impact Value are analysed in the sensitivity analysis section 7.4 below.

7.2.2 ABC model

In fulfilling the third objective of this study which sought to know the extent to which a combination of Bayesian approach and a cost model could improve cost estimation, ABC cost model for the offshore drilling sector is developed in this section. The ABC approach assigns cost to drilling activities in a more logical manner on the basis of cost per hour for each activity and a relationship between the activity cost and the project is established using Microsoft excel for such analysis (Niazi *et al.* 2006, Qian & Ben-Arieh 2008, Yongqian *et al.* 2010, and García-Crespo *et al.* 2011). Within the context of this thesis, data from three offshore fields is used for developing the ABC model. Linearity assumption is used to test the relationship between the dependent and independent variables for the ABC model. The Table 7-2 below presents the average offshore deepwater drilling cost data in Sub-Sahara Africa from 2005 to 2015 from the three offshore drilling fields: Jubilee field in Ghana, Erha offshore field Nigeria and Luanda offshore field in Angola. For the purposes of the ABC model, the average cost for services, rigs, logistics, equipment and materials and administration from the three fields were used. From the table 7-2, it can be seen that on average an offshore deepwater drilling well project costs approximately $15million USD in Sub-Saharan Africa.

Table 7-2: Offshore deepwater drilling cost for sub-Sahara Africa (million USD)

Year	No Wells	Services	Rigs	Logistics	Eq&Mat	Admin	Estimate
2005	22	58.1	56.44	23.24	16.6	11.62	166
2006	23	74.2	72.08	29.68	21.2	14.84	212
2007	23	77	74.8	30.8	22	15.4	220
2008	38	215.46	209.3	86.18	64	40.66	615.6
2009	22	136.5	132.6	54.6	39	27.3	390
2010	19	122.5	119	49	35	24.5	350
2011	43	277.2	269.28	110.88	79.2	55.72	792
2012	34	192.85	187.34	77.14	55.1	38.57	551
2013	33	191.8	186.32	76.72	54.8	38.36	548
2014	6	31.9	31	12.77	9.12	6.41	91.2
2015	6	33.95	32.98	13.58	9.7	6.79	97
Total	269	1411.46	1371.14	564.59	405.72	280.17	4032.8
Av. cost		5.25	5.1	2.1	1.55	1.04	15.04

Source (Tullow 2016, ExxonMobil 2016, and Shell 2016).

The average cost for an offshore well shown in table 7-2 is further broken down in table 7-3 to display the drill activity cost-DAC (total drilling activity cost /drilling time duration), activity time (AT) is the total man/machine hours used in drilling which on average in 30days or 720hours which is in accordance with the offshore industrial practice hence all calculations were made using the estimated 30 days (720hours) as the average time required to complete an offshore deepwater well in Sub-Sahara Africa (IEA 2013 and IHS 2015). From table 7-3 below, total activity cost (TAC) is calculated by multiplying DAC by AT. Overhead cost for this period 2005-2015 for each producing country has a cumulative average of 30% which can be given by finding 30% of the TAC. The final cost FDC is given by adding TAC to OC as shown in the table below.

Table 7-3: ABC calculation for sub-Sahara Africa offshore drilling (2005-2015)

Drilling Activity	Drilling Activity Cost/hour (DAC)	Activity Time(duration) (AT)	Total Activity Cost (TAC)	Overhead Cost (OC)	Final Drilling Cost (FDC)
Services	0.007291666	720hrs	5.25	1.575	6.825
Rig	0.007083333	720hrs	5.10	1.530	6.630
Logistics	0.002916666	720hrs	2.10	0.630	2.730
Equip/Materials	0.002152777	720hrs	1.55	0.465	2.015
Administration	0.00144444	720hrs	1.04	0.312	1.352

Source: (Tullow 2016, ExxonMobil 2016, and Shell 2016)

Using the cost data from the ABC calculation in the table 7-3 above, it can be seen that services and rig activity costs accounted for more than 65% of the entire offshore deepwater drilling cost followed by logistics and cost of equipment's and materials. Again, from the ABC table above, any changes in the cost activity time or duration changes the cost for everything.

To determine the relationship and impact of overhead cost on cost activity, a linear equation was used to test this. Figure 6-5 measures the relationship between the overhead cost and total activity cost. The figure below shows a linear relationship between OC and TAC. The ABC model is given by **y=3.3333x + 4E-15** where x represents the cost of each drilling activity. The intercept of x suggests that for every activity cost there is a rise of 3.333 overhead which means the higher the value of x the higher the overhead cost will be. Thus as the cost of drilling activity increases, overhead cost moves in the same direction.

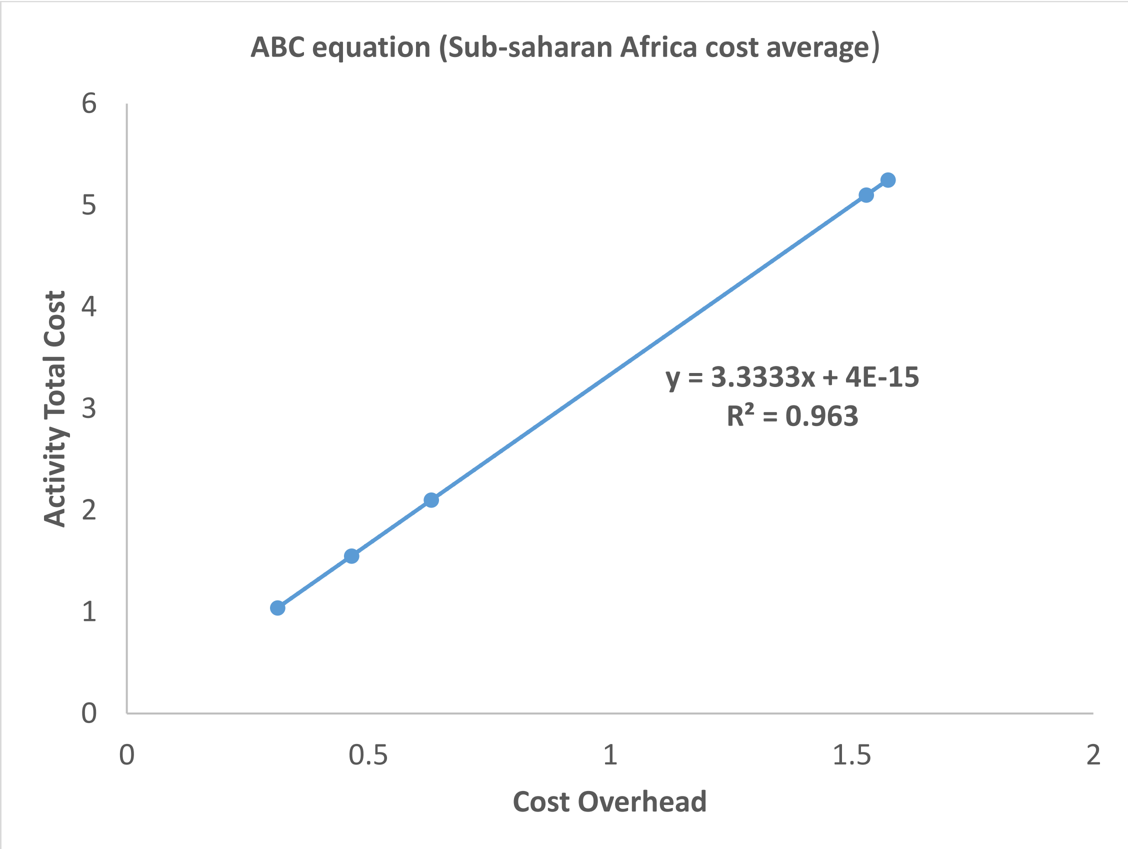


Figure 7-5: ABC equation for sub-Saharan Africa offshore using data from table 7-3

From the data used for the ABC equation, the percentage of the variation in the cost of drilling activity explained by the model is very high. The R^2 indicates the variability of the response data around its mean hence an R^2 of 0.963 from figure 7-5 signifies a strong relationship between activity cost and cost of overhead such that any rise in activity cost increases in overhead cost as well. The performance of each cost variable can easily be assessed and measured against planned budget using the ABC model. To make up for the short falls in ABC as discussed in earlier sections in terms of its inability to elicit probabilistic responses on external factors that have a huge impact on drilling cost, the next section shows how the ABC results and results from the developed Bayesian are combined to generate project cost estimate.

7.2.3 Integrated model from Bayesian and ABC estimation methods

The Bayesian Network model developed in section 7.2.1 focusses on deriving probability distributions from experts through elicitation process based on known unknown variables with limited or no data as defined in the concept definitions in section 1.7. The ABC equation in section 7.2.2 on the other hand, handles the "known known" variables whose cost are determined by the market. Therefore, in achieving a robust cost estimation model for the offshore deepwater drilling industry from these developed models, it is important to demonstrate how to integrate them by following the step-by-step guide explained in the next paragraphs.

Step 1: Identify the relevant cost factors for offshore drilling.

Assemble all available data (known knowns) on cost factors and establish which of the other cost drivers (known unknowns) with the strongest influence on cost overrun require elicitation. Use available cost data to develop an ABC equation Yongqian *et al.* (2010), and García-Crespo *et al.* (2011) in the form (y=mx +b) following the approach in section 7.2.2. and the example from table 7-3 and figure 7-6 above.

Step 2: For each cost factor in the ABC, calculate the impact of each cost driver on them.

The goal of this analysis is to understand the effects of the cost drivers on the cost factors. For instance, using cost factors such as services, rig, logistics, equipment and materials, and administration, step 2 examines how cost drivers such as politics, delays and currency depreciation affect each of the former as discussed earlier. To do this the following steps can be followed:

- ✓ For each of the cost factors identified in ABC model use the elicitation process developed in section 5.5 of chapter 5 to get the probability of the cost drivers affecting their final cost
- ✓ Using equation 6.5 from the Bayesian model developed in section 7.2.1 of this chapter, calculate the joint probability of the experts for each cost driver's impact on the cost factors
- ✓ Calculate the extra cost that needs to be added to each of the cost factors by multiplying the joint probability to each of the cost factors to determine the cost figures from the cost drivers.
- ✓ Add the results of the impact of the cost drivers to the cost factors (primary cost data).

Step 3: Combine Bayesian Network and ABC results.

Use the combined results as the cost estimate for the project under consideration. In relation to this research, Bayesian Network model which takes care of the known unknown variables or cost drivers with ABC model that represent the known knowns or the cost factors help to produce robust cost estimates for the offshore deepwater drilling sector as demonstrated in the validation and verification section that follows.

7.3 Model validation and verification

Accurate cost estimation is important for making many offshore drilling project decisions. In view of this, any cost estimation model made for this purpose is required to pass verification and validation test to prove the validity and reliability of such model. Therefore, the combined Bayesian and ABC model is verified and validated based on the assumptions, exceptions and the input-output results of the model.

7.3.1 Assumption

A basic linearity test conducted using the data in table 6-2 and the ABC model from figure 6-5 gave an R^2 of 0.963 which showed that x (cost factors) are linearly related to y (cost of drilling). Statistically, the R^2 of 96% is an indication that the independent variables (x) predominately explains the dependent variable (y) which fulfils the linearity assumption on which the ABC model was developed and satisfies the acceptable standard for an ABC model. Again, since ABC model is usually expressed as in a linear form, the equation **y=3.3333x + 4E-15** from figure 6-5 achieves such requirement and capability. Also, the process used to develop the ABC model as explained in section 7.2.2 above is internally complete, consistent, and adequate enough to support further advancement of the model (Pace 2004).

7.3.2 Exceptions

An exception to the model is anything that can cause the model to function in an unpredicted way or produce wrong results either through wrong used of data or wrong data format used. The developed Bayesian model is based on probability and hence any data not represented in that format would not yield the intended outcome from the model. Therefore, as part of the exception handling, elicited responses in the form of numbers or words cannot function in this model unless transformed into probabilities by the model handler. Again, the ABC function of the integrated model demands that the cost variables (dependent and independent) have a linear relationship and hence failure to establish that inherently discredit the results of the model. This was proven in the equation **y=3.3333x + 4E-15** where y (drilling cost) is the dependent and x the independent variables. Equally, violation of the existence of a causal relationship and conditional independence among the variables for the Bayesian model also can cause the model to produce wrong results.

7.3.3 Input-output results

In validating the model results, elicited judgments data (primary data) from Ghana, Nigeria, and Angola using the improved elicitation process developed in this research was used. Demographics and analysis of the data have been explained and analysed in detail in section 6.5.2 above. Experts were asked to analyse causes of cost overrun and to use their experiences to express the probability of cost drivers such as politics, delays, and depreciation of currency contribution to the problem. The inferences from the experts were compared with existing data in the literature and were found to be consistent to be accurate and reliable (IEA 2016). Table 7-4 contains the yearly aggregated average on how the probability of politics, delays and currency depreciation against the US dollar contribute to offshore drilling cost overrun. From the data, it inferred that on average 35% of offshore drilling cost overrun is as a result of politics and delays while 30% is influenced by weak local currency against the US dollar.

Table 7-4 Expert Judgement on Politics, Delays, and currency depreciation for sub-Saharan Africa

Year	Probability of Politics	Probability of Delays	Probability of currency depreciation vs $
2005	40	20	40
2006	35	30	35
2007	38	30	32
2008	40	30	30
2009	38	33	29
2010	35	31	34
2011	38	37	25
2012	32	32	36
2013	33	31	36
2014	34	34	32
2015	29	29	42
Averages	**35**	**35**	**30**

Source: (Primary data collected)

Therefore, given that politics is (A), delays (B) and currency depreciation (C) where P(A)=0.35, P(B)=0.35 and P(C)=0.30. The individual and joint impact of these three factors on drilling cost can be determined using equation (6.5) from the Bayesian Network algorithm.

Using the formula:

P(A,B,C) = [P(A/B,C)P(C/B)P(B)]*[P(B/C,A)P(A/C)P(C)]*[P(C/A,B) P(B/A)P(A)] the joint and conditional probabilities of A, B and C can be expressed below in figure 7-6.

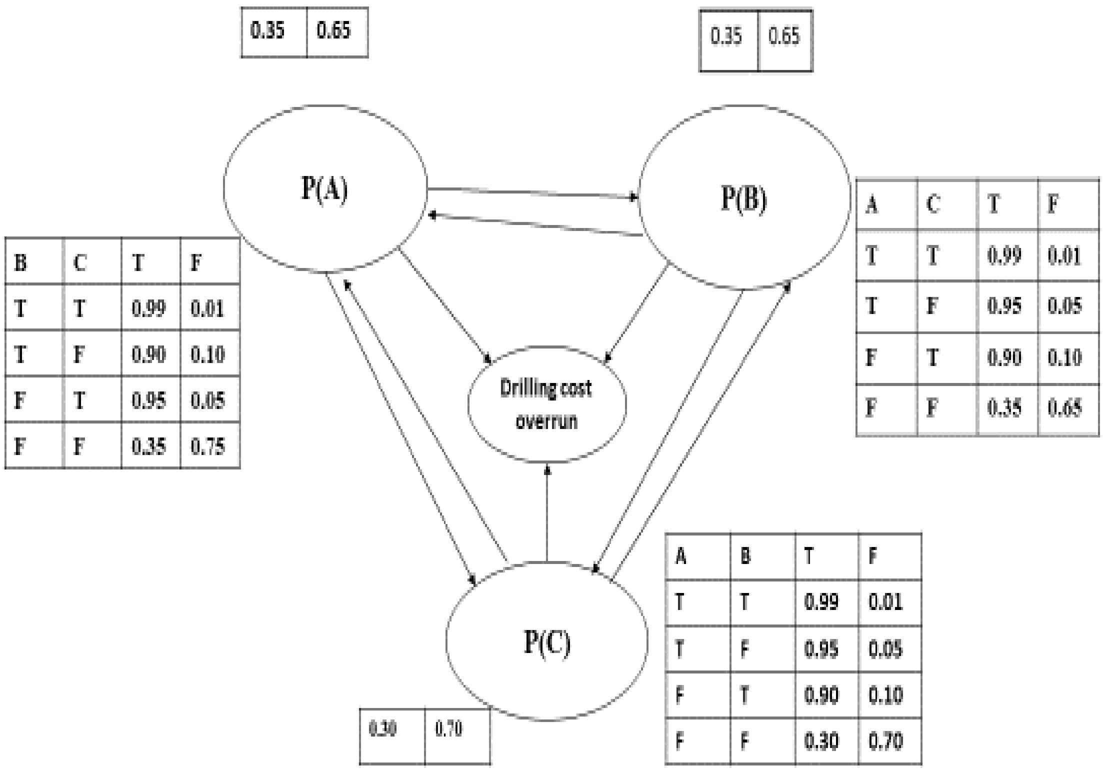


Figure 7-6: Probabilities distributions of cost drivers

The figure 7-6 explains the individual probabilities of A, B, and C and present all the conditional probabilities for each. Using the average probabilities figures from table 7-4 the conditional probabilities were calculated suing the Graphical Models Network Software which predicts the impact each variable has on other with a known probability. In reference to the calculations of the probability events in appendix A-8, the joint probability is given as:

P(A,B,C)=[0.99*0.90*0.35]*[0.99*0.95*0.30]*[0.99*0.95*0.35]

=[0.32]*[0.28]*[0.33]

=0.295 or 29.50%

The joint probability of 29.50 % represents the extent to which expert judgment on the 3 elicited variables can explain the existing cost overrun in drilling. This percentage is used to calculate the Bayesian cost results by finding the difference between the actual cost of drilling and the primary cost of the cost factors using the joint probability 29.50%. The probability results indicated that the sub-Saharan offshore drilling cost overrun can be reduced by 29.50% by finding the value of this in monetary terms and adding it on to the primary data cost as explained in table 6-5 below using the Bayesian model. Using the averages of politics, delays, and depreciation of the currency in table 6-4, the proportion of each cost driver from the joint probability of 29.50% is 10.33% for politics (35/100*29.50%), 10.33% for delays (35/100*29.5%), and 8.84% depreciation of currency (30/100*29.50%). Table 6-5 compares the results of existing models in the oil industry, the actual drilling cost and the new model results. From the table 6-5, the actual cost for drilling an offshore well in sub-Saharan Africa is averaged at $15.04millionUSD while existing cost models such as parametric, Monte Carlo and others estimate the cost at $10.75millionUSD. This shows an overrun of approximately 28% as against 25% of the new model developed by the researcher which saves on average approximately $1.5milionUSD on drilling activities. The performance of the new model in estimating offshore deepwater drilling cost is 3% more accurate than the existing cost models used by the three oil operators under consideration. According to Roy (2003), Shehab and Abdalla (2001), and Qian and Ben-Arieh (2008), one of the ways to reduce cost overrun is to have a model that predicts cost estimates more accurately. On the basis of the criteria given by the aforementioned authors, this model achieves that purpose as it provides better estimates compared to the old models reviewed in this study.

Table 7-5: Input-output results of developed model (amount in million USD)

Year	Old model results	Actual drilling cost	Prior (Variance)	ABC	New model Results ABC+ Bayesian
2005	116.53	166	24.73	101.24	125.97
2006	156.28	212	24.86	132.79	157.65
2007	154.59	220	29.06	130.86	159.92
2008	451.36	615.6	74.02	381.90	455.92
2009	294.57	390	43.45	251.62	295.07
2010	249.41	350	48.19	211.20	259.39
2011	553.21	792	110.39	468.73	579.12
2012	394.29	551	72.35	328.13	400.48
2013	391.82	548	72.24	326.20	398.44
2014	63.84	91.2	12.68	51.45	64.13
2015	66.95	97	13.02	55.65	68.67
Cost per well	**10.75**	**15.04**	**1.95**	**9.07**	**11.02**

NB: cost average was derived from the 269 wells considered.

Again using data in table 7-5, a year after year comparison of the new model cost estimates against the old model and actual drilling cost from 2005-2015 further proved that the new cost model delivers a better estimate than the old cost estimation model.

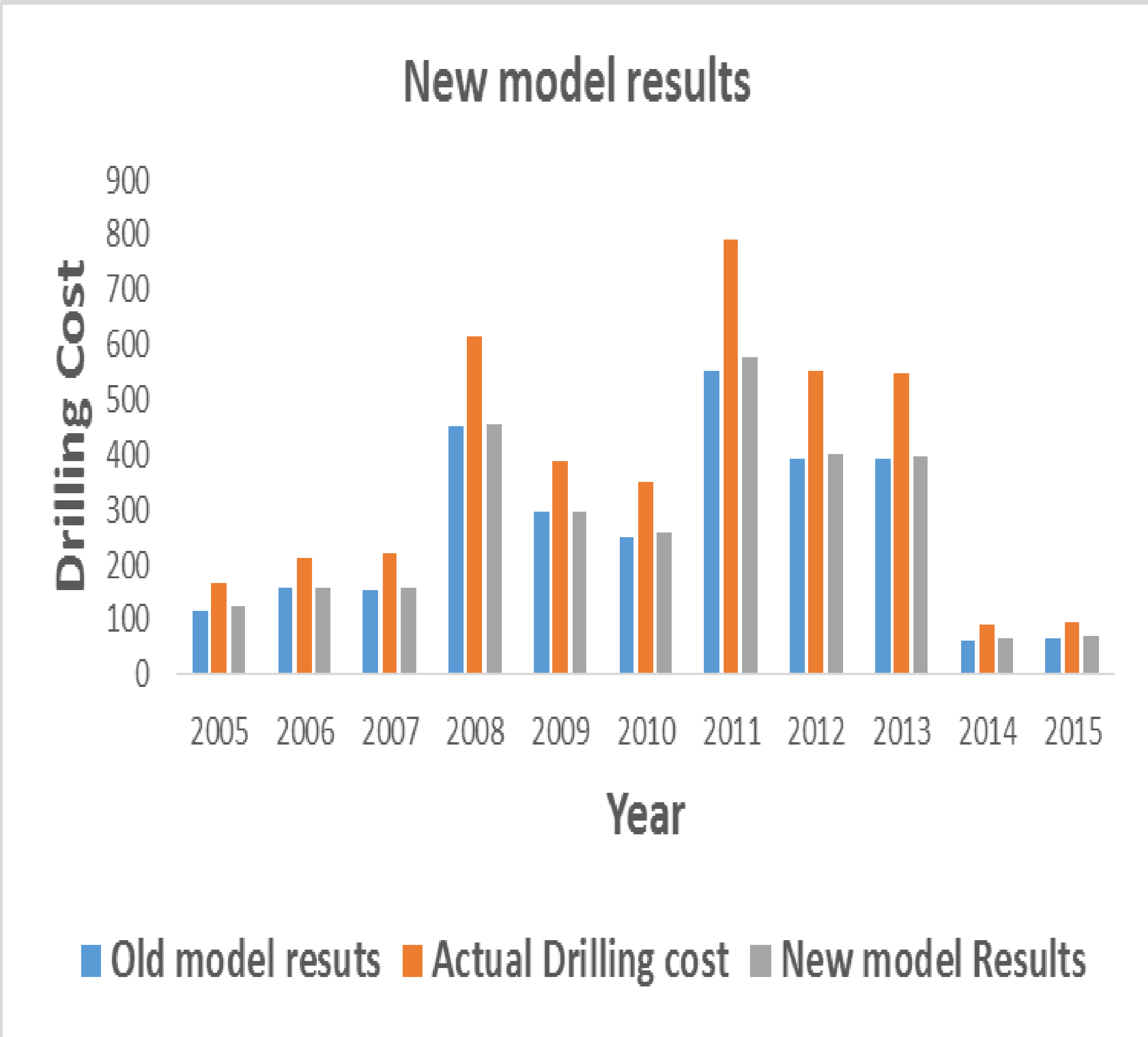


Figure 7-7: Year by year performance of new estimation cost model.

Figure 7-7 above show consistently from 2005 to 2015 that the new cost estimates are more accurate than the results from the old cost estimation models used by operators in the sub-Sahara Africa. Though the results still do not precisely estimate the exact cost of offshore drilling project notwithstanding its improved cost estimates compared with the old cost models is a huge step towards reducing cost overrun in the oil and gas industry.

7.4 Sensitivity analysis of model inputs

To see how sensitive, the cost estimates from the model respond to changes in the cost drivers such as politics, delays, and depreciation of currency, the drilling cost average per well for the Sub-Sahara Africa in table 6-5 above was used for the sensitivity analysis. The Bayesian Impact Value of 20% is used as the median for the analysis while the cost estimate value is calculated for any increases in the BIV from 10-20% above the median value and a decrease of 10-20% below the median given. Table 7-6 summarises the model results for any increase or decrease of joint probability or experts or the BIV above the median 20% and their corresponding overrun percentages when compared with the actual Sub-Sahara cost per well of $15.04million USD.

Table 7-6 Sensitivity Analysis Table

Sensitivity value (%)	Model results	% overrun to Actual cost
+20(40)	13.33	11.37
+10(30)	12.12	19.41.
0 (20)	11.02	25.00
-10(10)	9.92	34.04
-20(0)	8.93	40.06

It is determined from table 7-6 that the sensitivity test portrays an increasing magnitude of change in the model results accuracy and decrease in cost overrun with

BIV of +10-20%. On the contrary, with BIV from -10-20% the model results deteriorate. In agreement with the minimum BIV suggested for the algorithm, it can be seen from the table above that when the joint probability falls below the minimum BIV of 20% to 10%, the model results estimated the average cost of an offshore well to be $9.92million which approximately represents 40% cost overrun a figure known to be the average sub-Sahara regional cost overrun (Kaiser 2009). The sensitivity analysis has demonstrated that a joint probability of 20% reduces the current cost overrun from 40% to 25% whereas anything below that is equal or above the current cost overrun average in the sub-Saharan region hence the proposed **≥20% BIV** is logically sound as a measure to ensure offshore deepwater drilling cost estimations in the sub-Sahara Africa are reasonably accurate.

Again, figure 7-8 below shows that Bayesian model parameters such as politics, delays, and depreciation of currency cause the greatest change in the model output.

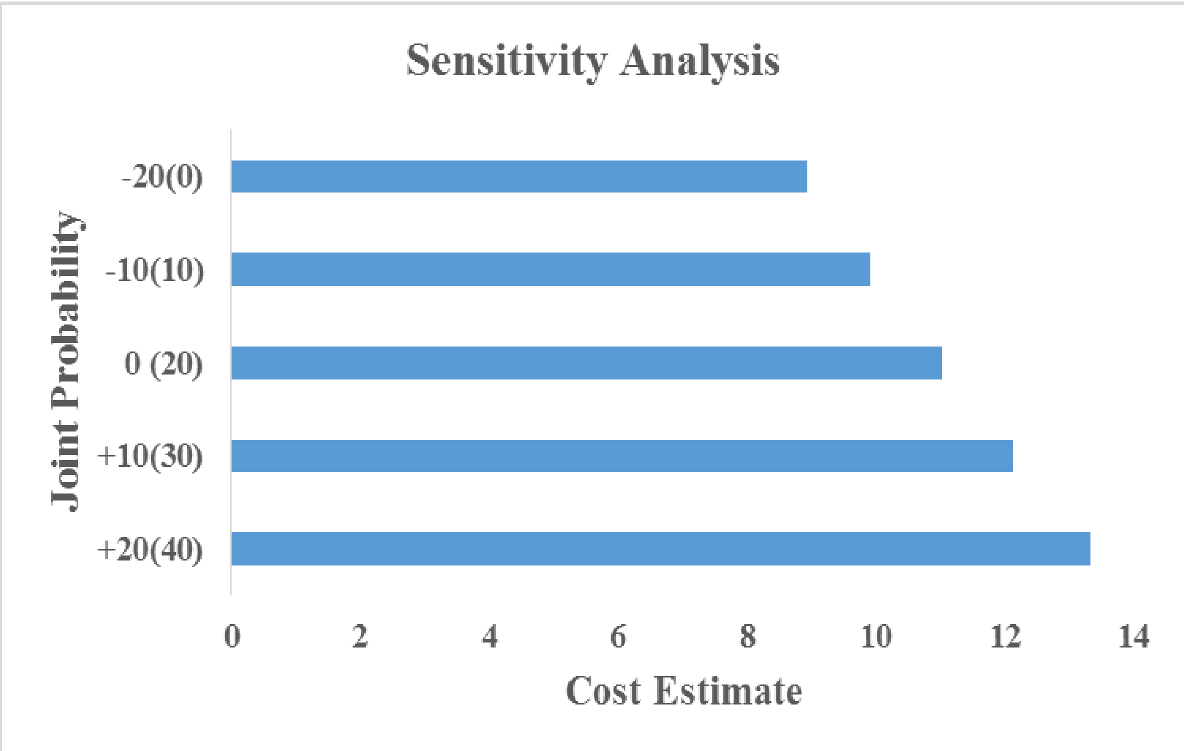


Figure 7-8: Sensitivity analysis results of cost estimate

As shown in the figure above, there is an increase in the cost estimates as the joint probability rises from 10% to 20% which demonstrates how sensitive an increase or decrease in any of the parameters used can affect the model output or results.

7.5 Chapter summary

The integrated robust Bayesian network and ABC cost model was developed and validated based on the assumptions, exceptions and the model input-output results. The new model input-output results showed an improvement of more than 13% of cost estimate compared with the old cost estimation models used by oil operators in the Sub-Saharan Africa when average offshore drilling cost data for the same region was used. Again, sensitivity analysis of the model parameters revealed that the ability of the model results to reduce cost overrun is sensitive to the rise or fall of the joint probabilities of experts on the impacts of politics, delays and the data on the depreciation of currency on offshore drilling cost.

Chapter Eight

RESEARCH RESULTS AND DISCUSSION

8.1 Introduction

This thesis concentrated on three core areas; understanding the causes of cost overrun in the offshore deepwater drilling operations in Sub-Saharan Africa, examination of the limitations of current cost models to make accurate cost predictions, and an investigation into the extent to which a combination of Bayesian approach and a cost model would improve cost estimation and reduce overrun. As established in chapter 3, it was discovered that the main research gap is the lack of a validated framework or model that can provide accurate estimations with limited data, precisely capture risk, factor probability results of all the cost variables in the offshore deep-water drilling operations into a model and can be suitable and applicable to the systems and operations of the industry. This thesis has demonstrated the importance of combining Bayesian Network approach with ABC estimation techniques to reduce cost overrun and to close the gap identified through the analysis of causes of cost overrun in the offshore deepwater drilling industry. Further analysis of the causes of cost overrun and the abilities of current cost estimation models in the offshore industry led to the realization of the capabilities of Bayesian Network approach to measure probabilistically the impacts of cost drivers such as politics, delays and weak local currency against the US dollar on drilling factors such as services, rig, logistics, equipment and materials and administration through expert judgement elicitation process due to limitation of data in the industry.

The Bayesian estimation technique was combined with ABC to form an integrated and robust cost estimation model that has the ability to reduce the cost overrun by more than half. As justified in section 4.7 in chapter 4, ABC model was chosen because of its superiority to provide traceable cost information for each drilling activity, its suitability, and applicability to the operation of the offshore drilling industry and the ability of the ABC model to support drilling decision making to reduce cost. The developed model was based on the idea that the ability to determine the cost of critical factors (known unknowns) using Bayesian techniques and the cost factors (known known) with ABC can lead to a much-improved cost estimation in the offshore deepwater drilling sector. The validity and reliability of the model were tested in section 7.3 in chapter 7 and proved that cost overrun can be reduced by 13%. This chapter further analyses the results of the model by using data from three offshore fields (Erha, Jubilee, and Luanda). Again, comparison of the results with past cost estimates is analysed and discussed in addition to integrative analysis of the research findings with the literature reviewed. Finally, the chapter reports on the applicability of the developed model to other industries and discusses the limitations of the study.

8.2 Analysis of model results

One major finding of the validated model developed is its ability to generate higher cost estimates compared to the existing cost models. From the input-output results in section 7.3.3, it was demonstrated that the use of expert judgment in cost estimations is one of the ways to reduce cost overrun in the offshore deepwater drilling industry given the data limitations that confront the industry. To justify how the model results meet the expectations of this research, the model is tested using three different primary data sets collected from experts on three offshore fields from the Sub-Sahara Africa. Subsequent sections highlight the patterns, relationship, and effects of each cost factor on offshore drilling cost using the results from the model developed. For emphasis, the analysis in this section is dependent on data from Luanda, Erha and Jubilee offshore fields

8.2.1 Analysis of Luanda offshore field

The offshore deepwater drilling projects cost in Angola is affected by politics, delays and high rate of currency depreciation as measured against the US dollar just like most other oil producing countries in the Sub-Saharan Africa (IEA 2014). Table 8-1 provides year by year probabilities of the impacts of these cost drivers on offshore drilling cost which is used to derive joint and conditional probabilities using the Bayesian model developed for analysis purposes. The probabilities in the table below were the expert's judgments of oil workers in an International Oil Company situated in Luanda-Angola. As shown in the data collection above, the primary data was compared with existing data from World Bank, IMF, and auditing firms such as KPMG and IHS on the impact of politics and delays on oil projects for the time period 2005-2015 to check for any consistencies or deviations (IEA 2014, KPMG 2015, and Central Bank of Angola 2016). Just as the sub-Saharan data in section 7.3.3 above, this data was collected using the improved Bayesian elicitation process and the same semi-structured questionnaire presented in the methodology above. It can be seen from table 8-1 that currency depreciation average from 2005 to 2015 is approximately 38% which suggests that project costs stand the risk of overrun by that depreciation percentage if they are not factored in cost estimates. Again the average impacts of delay and cost of politics to projects for the same period are 37% and 25% respectively.

Table 8-1 Expert Judgement on Politics and Delays and currency depreciation data on Angola

Year	Politics effect on cost %	Effects of delays on cost %	Currency dep. Effect on cost	Kwanza vs dollar dep.
2005	35.00%	25.00%	40.00%	89.23
2006	37.00%	24.00%	39.00%	80.08
2007	37.00%	21.00%	42.00%	74.82
2008	42.00%	27.00%	31.00%	75.17
2009	40.00%	26.00%	34.00%	89.15
2010	38.00%	31.00%	31.00%	92.41
2011	39.00%	25.00%	36.00%	94.93
2012	36.00%	26.00%	38.00%	95.80
2013	34.00%	29.00%	37.00%	97.61
2014	35.00%	26.00%	39.00%	102.94
2015	33.00%	21.00%	46.00%	134.64
Average	**37.00%**	**25.00%**	**38.00%**	

Source (Primary data source, and Central Bank of Angola 2016)

In estimating the drilling cost of an offshore well in Angola, the elicited data in table 8-1 above and appendix A-1 (primary cost of drilling factors) data from Luanda offshore field were used. The ABC model was determined by following the approach discussed in section 7.2.2. Using excel, the cost per hour and the total cost for each drilling activities listed in appendix A-1 (services, rig, logistics, equipment and materials and administration) were used to generate the ABC equation **y=0.301x – 0.001** in figure 8-1 below.

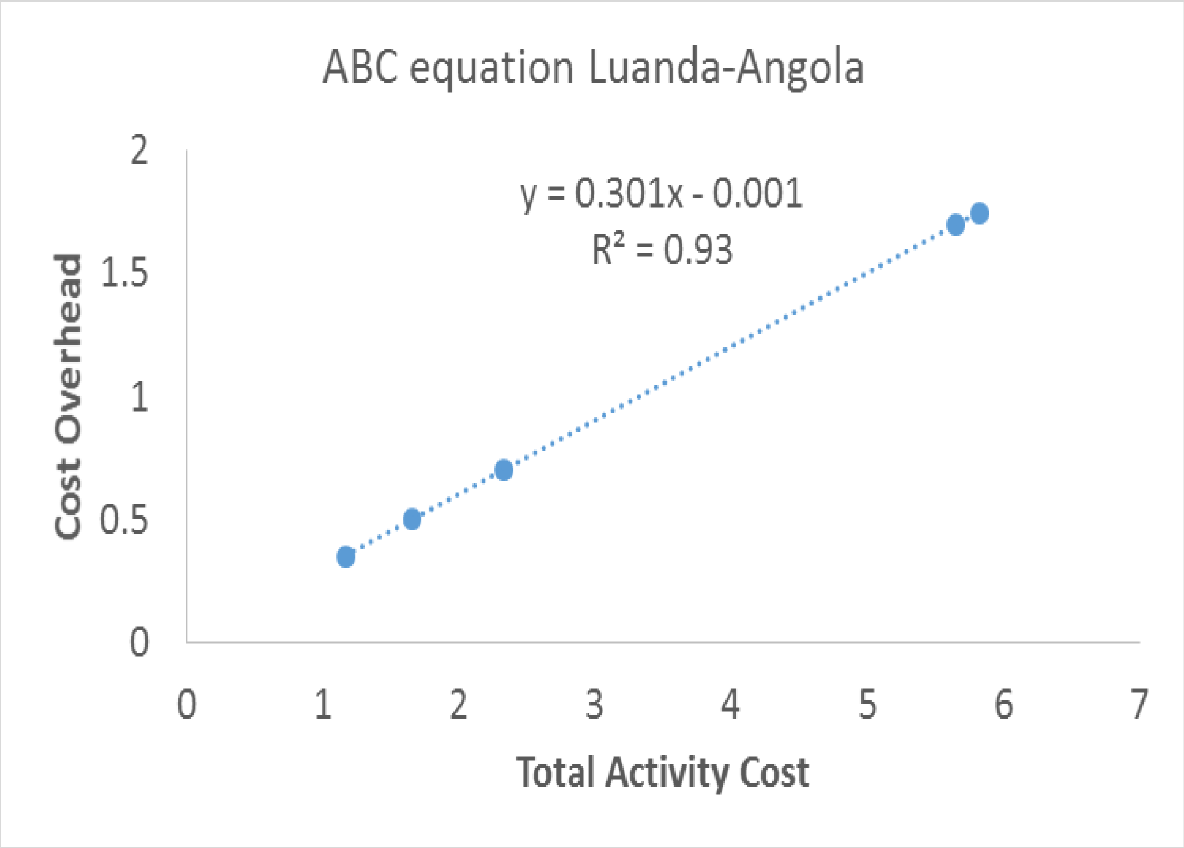


Figure 8-1. Luanda ABC Equation

The Bayesian model used the probabilities in table 8-1 to determine the posterior for each year using the previous year cost overrun percentage as the prior. Table 8-2 below shows the results from the integrated model developed and compares with the old estimates and the actual cost of offshore drilling. To determine future cost of projects in Angola offshore drilling industry using this estimation model, projected market cost of known cost factors can be used for developing the ABC equation by following the approach discussed whiles the elicitation process developed in chapter 5 should be used to derive joint probabilities of cost drivers associated with the project. The cost overrun figure in the period of estimation should be used as the first prior which is multiplied by the joint probability to arrive at the posterior of Bayesian results before it is added to the ABC results to make up the project cost estimate.

Table 8-2 Luanda offshore model results (cost in millions of USD)

Year	No of wells	Old model results	Actual drilling cost	New model results
2005	4	35.00	48.50	37.70
2006	2	15.00	21.00	16.10
2007	1	69.00	96.00	75.30
2008	9	61.00	87.00	67.60
2009	7	130.00	183.00	141.50
2010	8	227.00	350.00	261.40
2011	12	250.00	368.00	265.40
2012	7	66.00	106.00	87.00
2013	5	134.00	185.00	143.00
2014	11	179.00	297.00	223.20
2015	14	210.00	347.00	255.00
Total	**80**	**1376.00**	**2088.50**	**1575.20**
Drilling Cost Per well		**17.20**	**26.10**	**19.69**

NB: 80 wells were used for this analysis

Table 8-2 above presents the old cost estimate and the actual cost of Luanda offshore drilling from 2005 and 2015 as reported in the yearly reports of the operating company. The new model results were derived using elicited judgments data in table 7-1 and the data in appendix A of this study. While appendix A-1 was used to model the ABC part of the integrated model, data in table 8-1 above was used for the Bayesian Network using equation (6.5) in chapter 7 to calculate the joint probabilities. Given the average probabilities of politics, delays and currency depreciation at 25%, 37% and 38% respectively, the joint probability P(politics, delays, dep currency) is calculated (see appendix A-9 for calculations).

Hence $P(A,B,C)=[0.90*0.95*0.37]*[0.99*0.90*0.38]*[0.99*0.95*0.25]$

$=[0.3164]*[0.3386]*[0.2351]$

$=0.2519$ or 25.19%

Results from the Bayesian Network suggests that the model explains 25.19% of the causes of the drilling cost overrun in the Lunda offshore fields. Specifically, politics contribute an average of 6.30% (25/100*25.19) of offshore deepwater drilling cost overrun whereas delays accounted for 9.32% (37/100*25.19). Again, depreciation of the Kwanza against the USD accounts for 9.57% (38/100*25.19) of the cost overruns from 2005 to 2015. From table 8-2, the average old cost estimate for a Luanda offshore well is $17.20million USD whereas the actual average cost is $26.1million USD depicting an overrun of 34.09%. Results from the new model estimate the average drilling cost for a Luanda offshore well at $19.69million USD which is 24.55% overrun. Hence the new model is approximately 10% more accurate than the old model estimate. This result is relevant for future cost estimations as it shows how lack of knowledge of these factors has affected cost estimations in the past. Again, another proof of the relevance of these results from this study is that it addresses specific causes of cost overrun that affects most of the oil producing countries in Sub-Sahara Africa which make the findings from this study applicable in this region. Moreover, the findings on Luanda offshore (Angola) is consistent with several reports on the impact of high depreciation rate of Kwanza against the USD making Angola one of the most expensive countries to invest (Trading Economics 2015, IMF 2015, and World Bank 2015).

In addition to the above discussion, the results influence cost estimation knowledge and provide understanding on how cost overrun problems can be handled. This has been demonstrated though the analysis of the individual impacts of politics, delays, and depreciation of currency on projects cost. In terms of politics, Angola which has been ruled by one person for more than 35 years is noted to have high political interference in oil projects and equally have high reported cases of bribes given to government officials before projects are executed (Transparency International 2015). Moreover, the figure of 19.2% representing the impacts of delays to cost overrun is consistent with the findings of Enshassi *et al.* (2009) who concluded that "delays are a threat to a project success and a big contributor to project cost overrun" and 60% of construction cost overrun in the Middle East and Africa. Therefore the results of this research serve as a good reference point for oil operators and future researchers in terms of understanding how to reduce cost overrun and improve cost estimations.

Analysis of the results of the new model as shown in figure 8-2 below portrays a consistent accuracy of more than 19% compared with the old cost estimates from 2005 to 2015. Equally, the results of the new model compared with the actual cost of the drilling costs for the years under review produced cost estimates that have high accuracy considering the global offshore cost overrun of more than 40% and the 38.80% the old models produce.

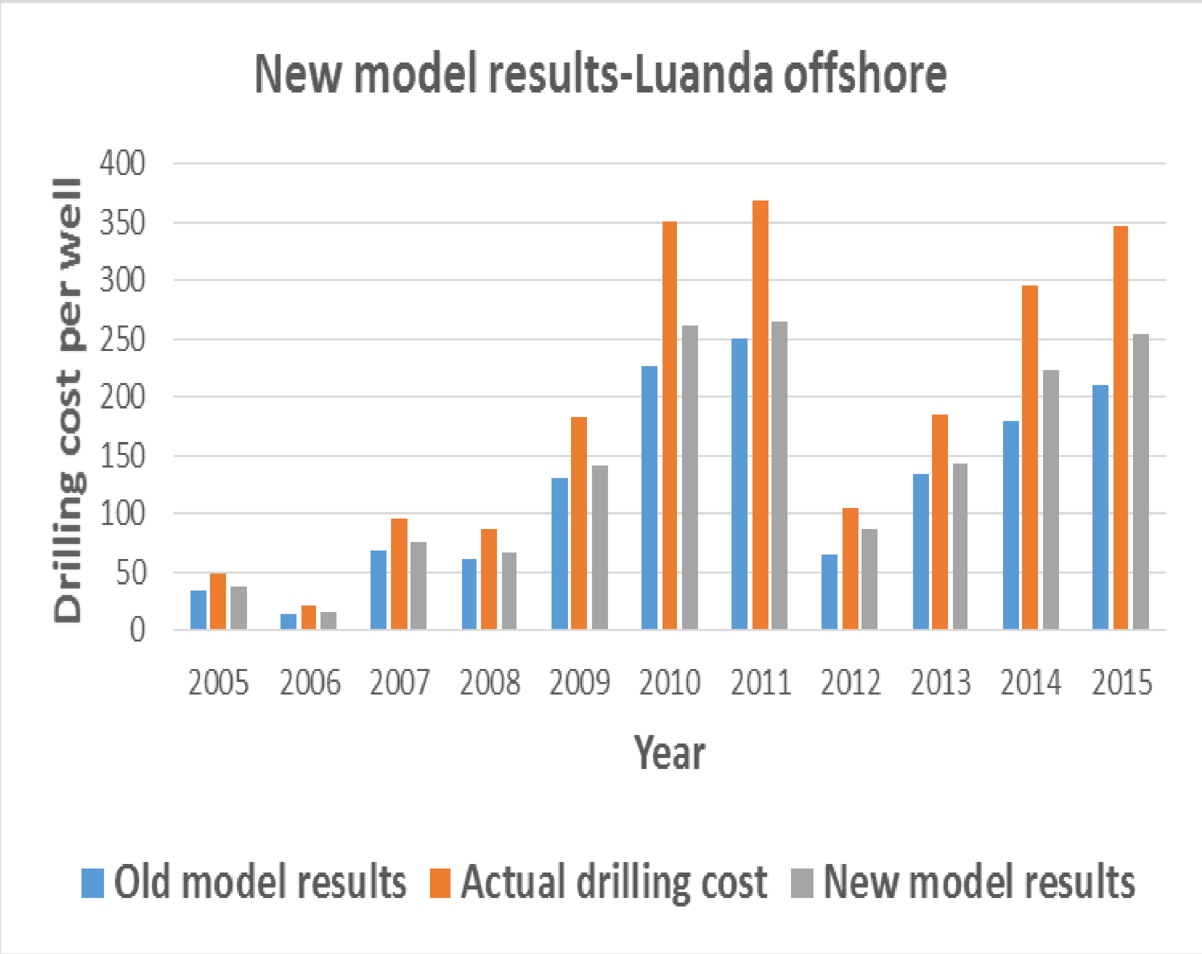


Figure 8-2 Luanda offshore results

The implications of the model results confirm the positions of Niazi et al. (2006) and Qian and Ben-Arieh (2008) that integrating two models has the ability to generate more improved cost estimates than one model. Particularly, considering the complex nature of the offshore deepwater drilling operations, the adoption of Activity Based-Costing Yongqian *et al.* (2010) and García-Crespo *et al.* (2011) as a suitable cost model, and Bayesian as one experiential technique O'Hagan (1994) and Congdon (2001) that can help reduce cost overrun is plausible.

8.2.2 Analysis of Jubilee offshore field

The efficiency of the developed model is tested and analysed using expert judgments on the contribution of politics, delays, and effects on currency depreciation of the

Ghana cedi compared with the US dollar on offshore drilling cost overrun over the period 2005 and 2015 similar to the way Luanda data was collected. Here again, the primary data collected was cross checked especially with other existing data on cedi depreciation against the dollar, politics, and delays for quality and reliability purposes (IEA 2014, KPMG 2015, Energy Commission Ghana 2015, Ghana Statistical Service 2015, and Central Bank of Ghana 2015). Table 8-3 shows the yearly aggregated probability average of the 15 experts from more than 2 oil companies in Ghana that participated in the elicitation process. It can be seen from the table that on average politics contribute 32% of all cost overrun in the Jubilee offshore drilling projects from 2005 to 2015 while delays account for 33% for the same time span. The impacts of the Ghana Cedis depreciation against the US dollar contributed to 35% of project cost escalations for the same period under review.

Table 8-3 Expert Judgement on Politics, Delays, and data on currency depreciation on Ghana

Year	Politics effect on cost %	Effects of delays on cost %	Effects of Depreciation on Cost	Depreciation of cedi vs dollar
2005	32.00%	33.00%	35.00%	21.98
2006	34.00%	32.00%	34.00%	15.22
2007	33.00%	32.00%	35.00%	8.50
2008	32.00%	34.00%	34.00%	14.15
2009	31.00%	33.00%	36.00%	29.79
2010	30.00%	32.00%	38.00%	16.80
2011	32.00%	35.00%	33.00%	17.22
2012	33.00%	33.00%	34.00%	19.44
2013	31.00%	34.00%	35.00%	17.95
2014	33.00%	33.00%	34.00%	68.75
2015	30.00%	32.00%	38.00%	73.95
Average	**32.00%**	**33.00%**	**35.00%**	

Source (IEA 2014, Ghana Statistical Service 2016, and Central Bank of Ghana 2016)

Equation (6-5) from the Bayesian model is used to determine the joint probabilities of politics, delays and currency depreciation on cost overrun using past overrun figures from 2005 to 2015 as prior for analysis purposes. From appendix A-10(calculation of all the probability of events) the joint probability of politics, delays, and depreciation of currency using data from table 8-4 and equation 6-5 is given as follows:

$$P(A,B,C)=[0.90*0.95*0.33]*[0.95*0.99*0.35]*[0.85*0.90*0.32]$$

$$=[0.2822]*[0.3292]*[0.2678]$$

$$=0.2488 \text{ or } 24.88\%$$

The figure 24.88% shows that on average offshore drilling cost overrun in the Jubilee filed can be reduced or explained if politics, delays and depreciation of Ghana cedi's are appropriately factored into cost estimation. The average contribution of politics, delays, and currency depreciation to Jubilee offshore drilling cost overrun for the period under consideration is calculated as (probability of cost driver/total probability of all the cost drivers multiplied by results from equation 6.5) Hence the contributions of politics, delays, and currency depreciation to cost overrun are 7.96% (32/100*24.88), 8.21% (33/100*24.88) and 8.71% (35/100*24.88) respectively. This suggests that the influence of each of these cost drivers can trigger a minimum of 20% cost overrun if not adequately catered for during cost estimation. Again, offshore drilling primary data(x) for Jubilee field in appendix A-2 is used to derive the ABC result in figure 8-3 below.

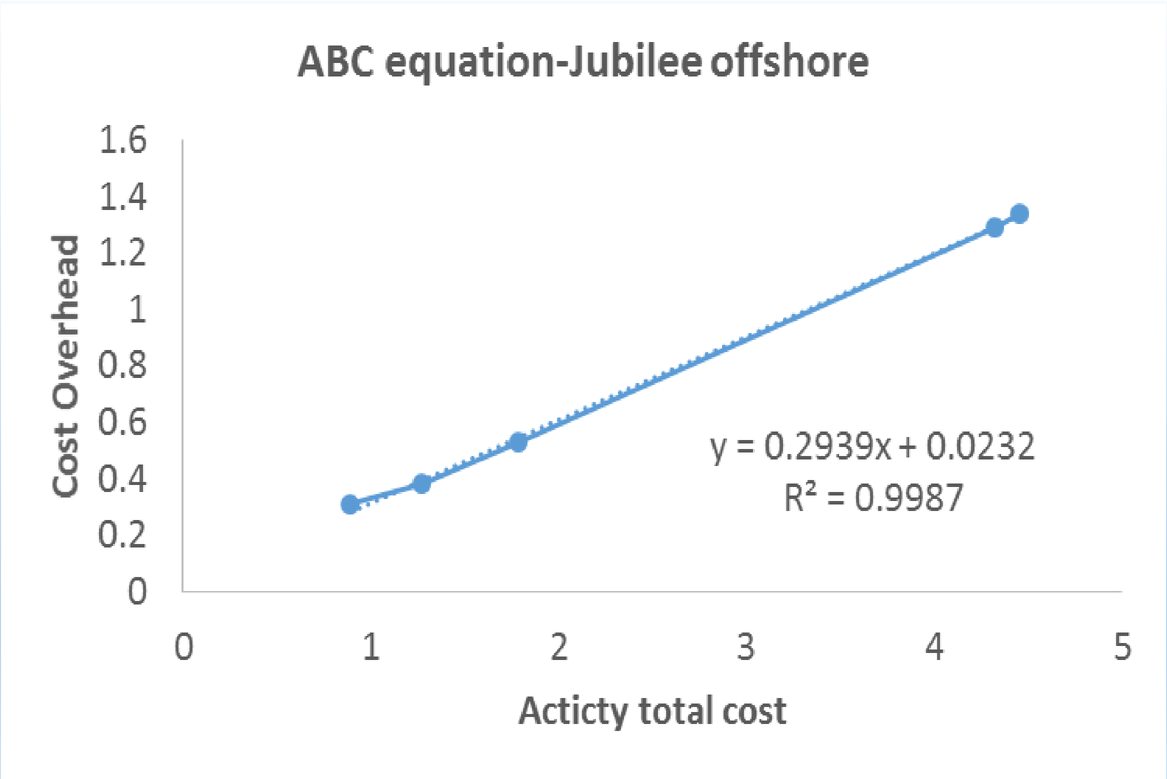


Figure 8-3: Jubilee offshore ABC equation

From the figure above, the ABC model is given by **y=0.2939x + 0.0232.** As illustrated earlier in this chapter, table 8-4 presents the results of the new model for each year and compares the model performance with the old model results and the actual drilling cost.

Table 8-4 Jubilee offshore model results (cost in millions of USD)

Year	**No of wells**	**Old model results**	**Actual drilling cost**	**New model results**
2005	2	26.30	35.00	29.63
2006	3	37.85	53.00	42.13
2007	7	93.00	121.50	103.75
2008	6	81.00	114.00	90.38
2009	4	53.20	95.00	67.25
2010	7	125.00	170.00	136.00
2011	6	105.00	166.00	125.00
2012	5	76.10	128.00	94.03
2013	18	260.00	366.00	274.38
2014	14	240.00	370.00	282.50
2015	8	81.70	140.00	111.00
Total	**80**	**1179.15**	**1758.5**	**1356.05**
Drilling Cost per well		**14.74**	**21.98**	**16.95**

Results from the new model in table 8-4 have proven that on average offshore drilling cost in the Jubilee field cost $16.95million USD whereas the old model used by the operators predicted an average cost of $14.74million USD. This thesis maintains that though the average old estimation model is greater than the sub-Sahara region average of $15.04million USD, however, it is still 10% less accurate compared with the new model results. It is important to emphasise that the integrated robust model developed has the ability to reduce Jubilee offshore drilling cost overrun from the existing 32.94% to 22.88% which is an improvement of 10.05% over the current model performance. These results from the ongoing analysis confirm that the ability to monitor and determine the effects of identified cost drivers such as politics, delays, and currency depreciation on offshore drilling activities affects cost estimation in the oil and gas industry. Hence the first two research questions that pursued to understand the causes of offshore drilling overrun and the extent to which the cost drivers contribute to the overrun has been answered with these results. Again, the last two research questions on the justification and ability of combination of Bayesian method and a cost model to reduce cost overrun has been proven credible in this study. As shown in the figure 8-4 below, there is a consistent improvement towards reducing cost overrun from 2005 to 2015 using the new model given compared with the old model estimate.

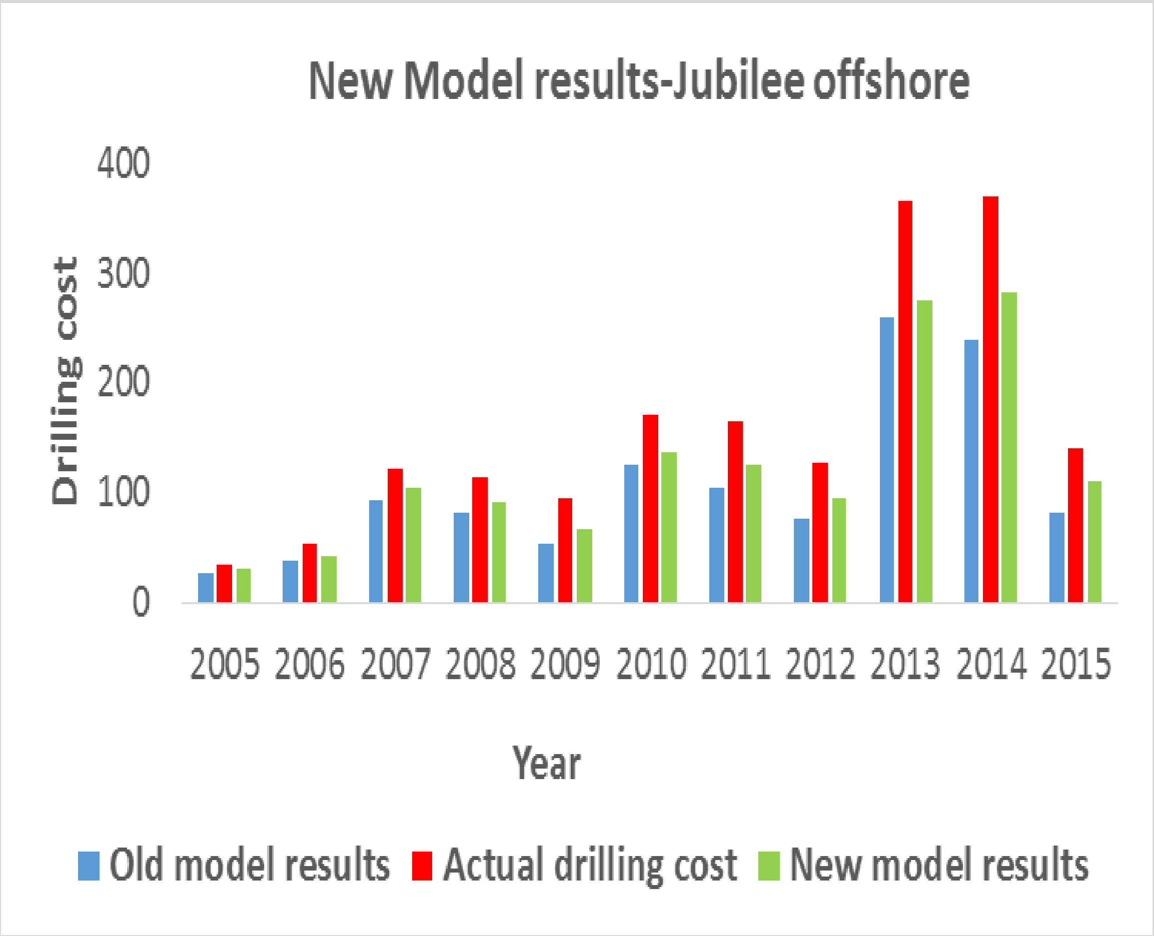


Figure 8-4 Jubilee offshore results

Although the actual drilling cost is still higher than both the old and new model developed as portrayed in figure 8-2 due to other factors still unknown, yet the new model provides hope of a new approach to reducing decades of cost overrun that has existed in the oil industry. Furthermore, the results in this study are more relevant considering the shocking decline of global oil prices from an average of $100 between 2008 to 2014 per barrel to below $50 in 2015 and early parts of 2016 due to low oil revenue to fund future projects. Moreover, the need for combined cost estimation techniques as a better approach to tackle cost overrun as suggested by Roy (2003), Qian and Ben-Arieh (2008), and Shehab and Abdalla (2001) is justified given the results in figure 8-2. The results influence knowledge and understanding of the operations in the offshore deepwater drilling industry by demonstrating that external factors have a huge impact on projects costs which require a more rigorous approach to handle.

8.2.3 Analysis of Erha offshore field

To analyse how sensitive the new model is to changing expert's judgments and probabilities of the efficiency and accuracy of the developed model were once again verified using data from Erha offshore field from Nigeria. As established in chapter 2 of this study about the consequences of failing to factor the impacts of politics IEA (2014) Transparency International (2015) and Aibinu and Odeyinka (2006), delays Elinwa and Johnson (2001) and Adnan *et al.* (2009), and depreciation of currency IMF (2014) and World Bank (2015) into cost estimation, table 8-5 below captures experts judgements on these critical cost factors. Similar to how the data for Luanda and Jubilee offshore fields were collected, Erha data was generated through the same process.

Table 8-5 Expert Judgement on Politics and Delays in Nigeria

Year	Politics effect on cost %	Effects of delays on cost %	% of Depreciation	Naira vs dollar dep.
2005	48.00%	23.00%	29.00%	31.30
2006	46.00%	26.00%	28.00%	33.21
2007	48.00%	25.00%	27.00%	26.67
2008	46.00%	28.00%	26.00%	36.58
2009	47.00%	27.00%	26.00%	33.85
2010	44.00%	28.00%	28.00%	29.82
2011	48.00%	26.00%	26.00%	33.76
2012	44.00%	27.00%	29.00%	23.35
2013	43.00%	27.00%	30.00%	29.90
2014	46.00%	28.00%	26.00%	30.15
2015	45.00%	25.00%	30.00%	28.65
Average	**46.00%**	**26.00%**	**28.00%**	

Source (Primary data source, IEA 2014, Central Bank of Nigeria 2016)

The average contribution of politics on offshore drilling cost is 46% which indicates that the existing cost overrun in the industry can be explained or eliminated or reduced by 46% if the effects of politics are correctly assessed and added during cost estimations. Delays and depreciation of Naira also contribute 26% and 28% of offshore drilling cost overrun respectively. From the table 8-5 above, the highest effects of politics on cost is 48% which was seen in 2005, 2007 and 2011. Again, the highest impacts from delays on offshore drilling costs were 28% in 2008, 2010 and 2014 whereas that of deprecation of the naira was 30% in 2015. Similar to the previous discussions in section 8.2.1 and 8.2.2 equation (6-5) from section 7.2.1 from the Bayesian model is used to calculate the joint probability of politics, delays, and deprecation of the naira against the USD using data from table 7-5 above. Again, using the cost overrun figures from 2005 and 2015 in appendix A-3 as prior information for the model, the average joint probability can be given as (see appendix A-11 for calculations):

$$
\begin{aligned}
P(A,B,C) &= [0.95*0.90*0.26]*[0.99*0.95*0.28]*[0.95*0.90*0.46] \\
&= [0.2223]*[0.2633]*[0.3933] \\
&= 0.2302 \text{ or } 23.02\%
\end{aligned}
$$

The result means that up to an average of 67.80% of all cost overrun in the Erha drilling projects from 2005 to 2015 can be reduced using the developed model. The individual probability contribution of politics to Erha offshore drilling cost overrun is averaged at 10.59.50% (46/100*23.02), the delay is 6.00% (26/100*23.02) while 6.43% (28/100*23.02) is accounted for by depreciation of the Naira against the USD. To appreciate the relevance of impact of the above cost drivers, data from appendix A-3 is used to derive results for the ABC model which is presented in figure 8-5 below

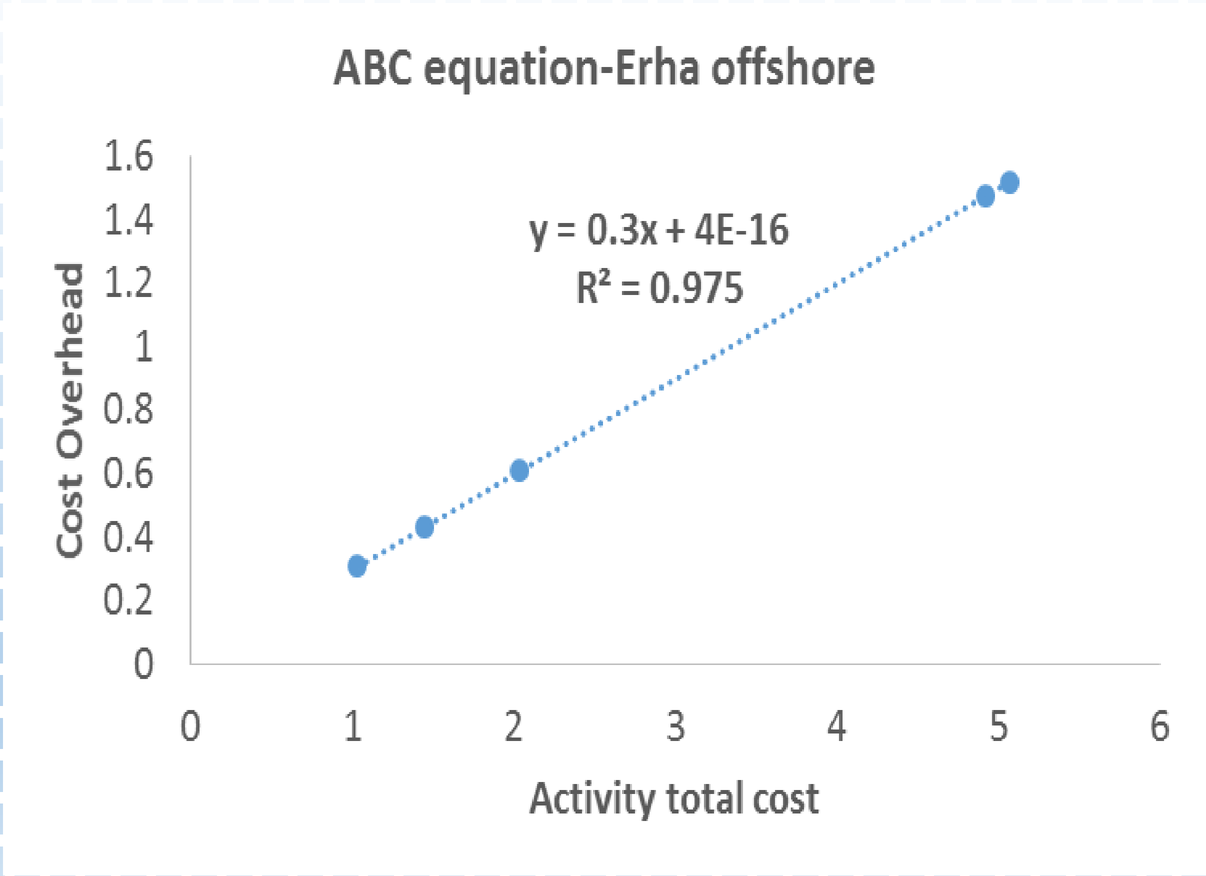


Figure 8-5. Erha offshore ABC equation

The above ABC model **y=0.3x+4E-16** is then added to the Bayesian model to form the integrated model. Appendix A-3 contains the primary cost of drilling activities such as services, gig, logistics, equipment and materials and administration as categorised in chapter 2 of this thesis. Table 8-6 below gives a breakdown of the integrated model results from 2005 to 2015 compared with results of old estimation models used by the operators and the actual cost for each year as specified on the table.

Table 8-6 Erha offshore model results (cost in millions of USD)

Year	No of wells	Old model results	Actual drilling cost	New model results
2005	6	85.00	131.26	100.61
2006	8	111.00	165.75	131.64
2007	8	127.50	183.00	150.31
2008	9	158.20	230.00	186.71
2009	11	167.30	251.00	195.69
2010	9	131.00	190.80	137.39
2011	8	150.00	210.00	177.00
2012	8	125.80	187.00	147.60
2013	10	125.70	198.00	148.34
2014	2	36.00	46.50	37.02
2015	1	12.00	19.40	14.15
Total	**80**	**1229.5**	**1812.71**	**1426.46**
Drilling Cost per well		**15.37**	**22.66**	**17.83**

From table 8-6 above, the existing model estimates the average cost of drilling an Erha offshore well at $15.37million USD which is less than the actual cost of $22.66million USD. This represents an overrun of 32.20% which means the existing cost estimation model if relied upon in its current state will present approximately $5million USD cost overrun for very well drilled at the Erha offshore field. The new model developed by the researcher offers a more improved estimate of $17.83million USD average for each offshore well drilling at Erha which reduces overrun from 32.20% to 21.30% showing an improvement of 10.90% on the old model.

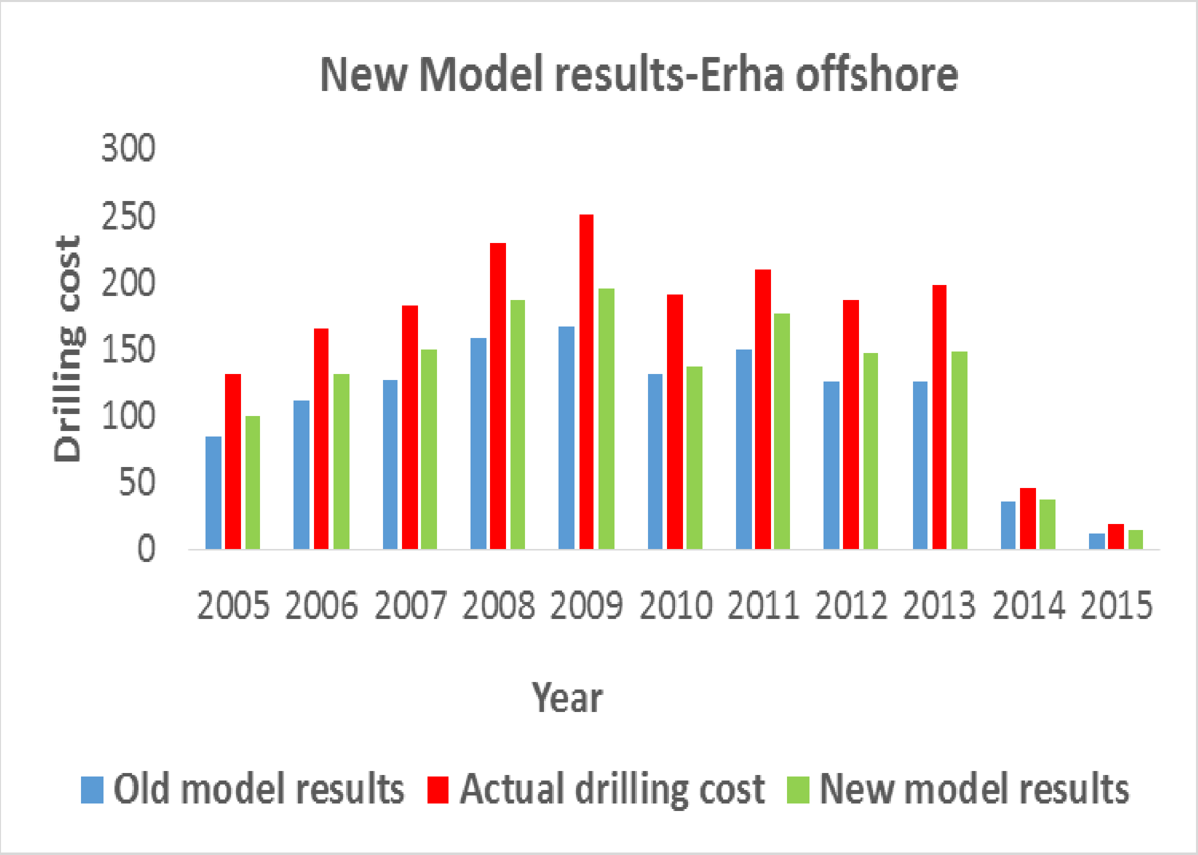


Figure 8-6. Erha new model results

The results from table 8-6 and figure 8-6 are relevant now and in the future for analysis and research as they provide insight into the efficiency of using a single cost estimation model and a combined technique while still acknowledging the need for continuous improvement because of the difficulty in eliminating project cost overrun. Again, in all the discussion done so far, it has been evident that cost overrun has not been eliminated but reduced because of many factors that cannot be determined or understood in the operations of the offshore deepwater drilling sector. This does not suggest in any way that it cannot be eliminated in the future with the availability of data and formulation of more advanced cost estimation models but in the current state of cost overrun this model has achieved its set goal. Therefore, it is a novelty and a major contribution to knowledge from this study as effects of politics, delays, and depreciation of currency as has been proven and analysed as key cost drivers in the offshore drilling industry in sub-Saharan Africa. This is because the results do not only inform oil operators on the best practices of estimation but also serve as an academic reference for the "infant" upstream oil and gas research. Section 8.2 has discussed the performance of the developed model from using data from 3 different countries to better appreciate the dynamics in these results, the next section compares the results and discussions by analysing the similarities and differences to justify the model approach and its suitability for the oil and gas industry.

8.3 Comparison of model results from the three offshore fields

A critical analysis of the performance of the new model developed by the researcher showed impressive results in all 3 offshore fields the model was tested. Luanda, Jubilee and Erha offshore fields showed considerable improvement in cost estimation by achieving a higher drilling cost estimate that is on approximately 17% higher than estimates from existing cost models used in each field. However, a comparison of the new model results in the existing old model estimate in each of the offshore field revealed that Erha offshore field cost overrun can be reduced by more than 64% given that the old estimate of $15.98million USD, developed model estimate of $21.10million USD compared with the actual cost per well of $26.10million USD as shown in table 8.2 above. From table 8-4 above the old estimate was $15.61million USD, new model estimate was $17.95 million USD compared with the actual average cost of drilling per well of $21.98million USD represented a reduction of Jubilee offshore drilling overrun by 37% whiles Erha's overrun was reduced by 50% given the old cost estimate of 15.37million USD, new cost estimate of 20.03million USD compared with the actual average cost per well of $22.66million USD as shown in table 8-6 above. Table 8-7 below summarises the averages for the old overrun, new overrun when the developed model is used and compares the percentage improvement of the new model against the old estimation models used at all the 3 fields.

Table 8-7 Summary of new model performance for the 3 offshore fields

Offshore field	**Old overrun**	**New overrun**	**Improvement of new model over the existing ones**
Luanda	34.09%	24.55%	9.53%
Jubilee	32.94%	22.88%	10.05%
Erha	32.20%	21.30%	10.90%

From the table 8-7 above, the new model improved estimation by 10.90% compared with the old model used by the operators using data from Erha as can be seen from the table. Again, Luanda was also 9.53% better than the old model whereas at Jubilee it was 10.05%. The variations in the model performance suggest the degree to which the cost drivers affect drilling cost in each of the countries. It also demonstrates that Erha (Nigeria) and Luanda (Angola) are more sensitive to the impacts of politics, delays, and depreciation of currency compared with Jubilee (Ghana). Again, the low joint probability for Jubilee from the discussion in section 8.2.2 compared with Luanda and Erha reduced the model performed as the Bayesian model is dependent on the probabilities given by experts. This supports the Bayesian Impact of a minimum of 20% joint probability suggested in section 7.2.1 as a good starting point for eliciting responses for the purposes of cost estimation in the oil and gas industry due to the huge nature of investment in the industry.

Despite the differences in the model results for the 3 fields discussed above, the model nonetheless was proven to have the ability to reduce cost overrun in the offshore drilling industry. This is because, despite the uniqueness of the countries involved in terms of economic performance, politics and all the other unique conditions that can affect project delivery, the model illustrated a significant improvement over the old model estimate. This confirms the robustness of the new model developed and its suitability and applicability for different project environment in the sub-Sahara Africa. Again, Jubilee field is the cheapest place for offshore drilling with an average cost per well of $21.98million USD (refer table 7-4) followed by Luanda $22.10million USD (refer table 7-2) and Erha $22.66million USD (refer table 7-6). The reasons for the differences in cost can partly be explained by the cost drivers discussed above. Also the fact that Jubilee field is one of the new discoveries in the world while Luanda and Erha are relatively older fields, oil servicing companies are more likely to enter such a market because of the financial prospects and potential of long contracts which increases supply far above demand thereby making Jubilee offshore drilling price lower than the other two. Moreover the inability of the new model to estimate accurately the actual cost of projects in all the 3 cases analysed confirms the findings of Yoe (2000) and Hall & Delille (2011) that because of the complex uncertainties surrounding the offshore drilling operations, it is impossible for any model to accurately predict the cost of drilling projects without any overrun and that the best solution is to bring it to the barest minimum.

8.4 Integrative Analysis of Findings with Literature Review

As part of the steps to evaluate how the results of this study influence knowledge and demonstrated an understanding of how to solve the problem being examined, an integrative analysis of the findings are measured against the literature reviewed in this work. Firstly, the findings of Elinwa & Joshua (2001), Poiate *et al*. (2006), Sambasivan & Soon (2007), Marzouk *et al.* (2008), Adnan *et al.* (2009), and Han *et al.* (2009) suggest that delays resulting from logistics, decision making, and project execution causes more than 20% of project cost overrun in Africa is not suspicious. Expert judgment data collected by IEA on the effects of politics on offshore drilling cost overrun used in this study has shown that delays cause an average of approximately 25% of all offshore drilling overrun using Luanda, Erha, and Jubilee as an example. Again, the recommendation of the critical need to assess the effects of politics and depreciation of local currency against the US dollar to adequately capture them during cost estimations by Poedjono *et al.* (2007), IEA (2014), IMF (2015) and Schlumberger (2015) have been highlighted in this study to be some of the critical factors that contribute to offshore drilling overrun in sub-Sahara Africa. The results of this study showed from the 3 offshore data analysed that politics, delays, and depreciation of currency against the USD on average can explain or reduce offshore drilling overrun by more than 65% which is consistent with the findings of Enshassi (2009), Yang and Wei (2010), and Rahman *et al.* (2013) who argued that more than 65% of the overrun in the sub-Sahara Africa oil and gas industry is primarily caused by political influence, poor economic performance by the host country and other external factors.

Analysis of current cost estimation models for the offshore deepwater drilling industry to provide a better understanding to the cost estimation practices in the industry showed there exist inherent limitations in these models to make accurate cost estimates with limited data. Thus, there was a clear indication that suggested that the reviewed models (current) lacked the ability to solve or reduce cost overrun in the offshore drilling industry. Aven *et al.* (2006), Niazi et al. (2006) and Qian and Ben-Arieh (2008) and many others argued for a combination of cost estimation techniques if the decade's problem of cost overrun is to be reduced as the past and current models have proved insufficient to possess the solution. An understanding of this informed the direction of this research to investigate the extent to which a combination of Bayesian technique and a cost model can deliver an improved cost model compared to the current cost models. The choice of activity-based costing was found to be the most appropriate cost estimation technique to be combined with Bayesian Network approach into a single model for this study because of its suitability and applicability to the oil industry coupled with its ability to provide detailed cost on each activity.

Moreover, it was established from the literature reviewed that the ability of cost estimation model to accurately estimate the known knowns (drilling services, logistics, equipment and materials and administration and management) and the known unknowns (politics, delays, depreciation of currency and other cost drivers) has the potential to reduce the sub-Sahara oil and gas industry cost overrun from 40% to less than 20% of the total cost of offshore drilling projects Liu and Samull (2008) and Kaiser (2009). The model developed by the researcher reduced cost overrun from an average of 35% to 17% using data from Luanda, Jubilee and Erha offshore fields from sub-Sahara Africa which has proven and justified the assertions of Lui and Samull, and Kaiser. Again, an evaluation of the correct use of Bayesian Network approach and expert judgment elicitation in the oil and gas industry showed the need to develop a tailored elicitation process for the industry. Therefore, an improved expert judgement elicitation process based on Bayesian approach was developed that can generate experts views in a probabilistic way using the Bayes rule. A step by step guide on how the process can be followed was adequately explained. Excluding the oil and gas industry, the developed model can be applied in other industries which are discussed in the next section.

8.5 Reaction to the model results by experts elicited

To test the usefulness of the developed model within the offshore industry, the researcher engaged with the experts used in collecting the data for this study to test their reaction. This was both to validate the usefulness of the results and also to complement the quantitative results with a more qualitative insight. From all the 31 experts interviewed, their reaction to the model results was very positive. All of them expressed their optimism about the potential of the Bayesian model developed to helping in reducing cost in the offshore drilling industry in Africa. In particular, all the experts agreed during the elicitation process that **"*having an expert based model that is elastic and robust and more scientific is highly recommended as this can help integrate the uniqueness and location features peculiar to each project*"**. Hence in the words of one expert, the integrated Bayesian and ABC model ***"is a good step as it is said in an African proverb…two good heads are better than one".*** Therefore, the model technique and methodology adopted for this model was seen as appropriate in dealing with the research problem. Again, commenting on the model results, some of the experts had this to say *"**an improvement of 10% prediction over our existing model estimate is a great gain. I strongly believe your model would surely help move the industry in a better position in terms of reducing cost in the offshore industry".***

Another expert argued that ***"cost overrun is all about uncertainty hence your model which uses probability is a huge step and a fantastic effort"***. This reaction suggests a contribution to knowledge by the findings of this research as it is evident companies can make 10% more savings if this model is used in their cost estimations either than their estimating estimation methodologies in the sub-Saharan region. Moreover, all the experts unanimously agreed after seeing the model results that ***"the integrated ABC and Bayesian model would definitely help especially since it factors expert judgments. The point is no project can be successful without relying on the lesson learned and experts' opinions especially in Africa which is not a controlled environment with the volatile economy"***. They concluded, ***"Your model has all the potentials to be a much more acceptable approach for the sub-Saharan Africa. This is really a good effort and is highly commendable!"*** Finally, the feedbacks received on the suitability and usefulness of the model results further confirm the novelty of this research as a robust framework that has the ability to minimise cost overrun in the deepwater offshore drilling operations in Africa. From the experts interviewed from the 3 countries, everyone was optimistic of the potentials of this model as can be seen from the transcript below " ***I believe your Integrated model can help improve the chance of getting a more accurate cost or closer to accurate cost compared to the actual as was evident in your research findings. So yes, I think this is a good step forward towards reducing cost overrun in the industry. That's really a good work***"

8.6 Applicability in other industries

The model developed in this thesis follows a standardised requirement as captured in chapter 3 of this study which makes it easily applicable and adaptable in different industries for the purposes of cost estimation. With the exception of the offshore drilling sector, the model can be used to make cost estimations in other projects in the upstream, midstream (transportation of crude oil) and downstream (refineries and sales) of the oil and gas industry. Azhar *et al.* (2008) and Kaiser (2009) argued that the causes of cost overrun are similar in every part of the oil and gas supply chain. Therefore, the developed model can easily be adapted to any project in the oil and gas industry in by only making changes to the cost factors that relate to the project in question. Similar to the above, the model is applicable to industries such as construction, highway and other public projects because project from each of these sectors is affected by cost drivers such as politics, delays, depreciation of currency discussed in this research. Again, the motivation for the elicitation process developed in chapter 5 is to make it easier for the model to be used in the context best suitable to the user which also make it possible for the model to be applied in different countries and other industries by following the guidelines provided by the researcher

8.7 Model criticisms and limitations

One of the common criticism of Bayesian approach and the model developed in particular is how to ensure expert views are non-biased and are as objective as possible. David & Baglioni (1988), Carlin & Thomas (1997), and Gelman *et al.* (2014) have all criticised the accuracy of subjective priors from experts and questioned the reliability of such posteriors. The seven-step improved elicitation process developed to offer a more robust option to reduce biases during elicitation. Thus the use of pre elicitation questionnaires for recruiting experts, provision of training before the elicitation exercise, and the use of more structured questions and techniques i.e. giving a range of answers to be chosen etc. are some of the measures considered to have the ability to minimise biases. While the Bayesian network model developed is fundamentally based on expert judgments it does not in any way suggest that the respondents were biased. Again, a critical look at the expert judgments used in the analysis of this study showed some consistency in the reported findings of the impact of cost drivers on cost overrun in the offshore industry which justifies the credibility of data used and the reliability of the model results. As a precaution in this study, the data used for the analysis were crossed examined and validated from more than 3 different entities to reduce biases as much as possible. In addition, as a guide for future cost estimations, section 5.2 of this thesis discussed extensively the potential flaws of relying on subjective opinions by suggesting training be given before elicitation and emphasized the need to structure both the questions and the elicitation to avoid any heuristics and biases. A limitation of the model is its inability to detect biased responses that can lead to erroneous results as is in the case of expert judgment based models but surely a robust elicitation process can minimise bias. Finally, this model can be generalised on the grounds of its theoretically underpin whereas the diversities in expert experiences and judgments can make the model results vary. This is consistent to the finding of the Bayesian scholars such as (O'Hagan 1994 & Congdon 2001 Garthwaite *et al.* 2006, Jenson 2007, and Fenton 2015)

8.8 Chapter summary

The chapter discussed the model results using data from 3 offshore fields in the Sub-Sahara Africa. Results from Luanda offshore field from Angola showed a reduction of cost overrun from 38.80% to 19.20% using the new model. Again the model reduced cost overrun of the Jubilee field in Ghana from 29% to 18.3% whiles Erha field from Nigeria was 11.60% from an existing average cost overrun of 32.20% from 2003 to 2013. A comparison of these results demonstrated the differences in the results could be explained by the uniqueness of each country in terms of how cost drivers affect each operation. Nonetheless, the new model developed was proven to have the ability to reduce cost overrun in the offshore drilling industry using the 3 offshore field's results as justification. Again, an integrative analysis of the results with findings in the literature was analysed. Moreover, the applicability of the model to other industries, criticism, and limitation of the research was discussed in this chapter.

Chapter Nine

ANALYSIS ON COST REDUCTION

9.1 Introduction to cost reduction analysis

There are other ways that can be exploited in reducing cost overrun in the offshore drilling industry. Lessons from the Bayesian results suggested that having a robust model is one of the ways to tackle the problem of cost overrun which is why the researcher provides another analysis on cost reduction using the recommendations of experts' data collected to ensure comprehensive solutions and options are available to the industry. In view of this, the chapter looks at issues such as value engineering, contracts and negotiations, cost reduction awareness and education, budgetary control, and cost optimization techniques as some of the methods that can be followed to reduce project cost in the oil industry.

9.2 Value Engineering

Value engineering which measures the function of a product or service to its cost was suggested by 16 out of the 31 experts interviewed in this research to be one of the ways cost can be reduced in the industry. The process involves gathering, measuring, analysing, generation, evaluating options and presenting of ideals to determine the best cost possible for a project with a given quality and lifetime (Gokharn 1998 & Dutta 2002). The justification given by the 16 experts showed that many at times functions of projects are not clearly defined which leads to paying more than expected for certain project functionality was worth considering. Cases were cited both at Jubilee field and Erha by some of the experts to substantiate the significance of this process. For instance, a case of Tullow oil having to spend £200million as a result of failing to determine the project function for a Floating Production Storage Offloading (FPSO) was cited while Nigerian National Petroleum Company (NNPC) reoccurring project cost overrun in time past identified value engineering as one of the causes by some of the experts interviewed. Overall, there is a clear indication that efficient value engineering before and during offshore drilling projects has the potential to improve project function or reduce the cost.

This has been confirmed by the performance of projects delivered at General Electric which is one of the very first companies that used value engineering. Evidence has shown that 4/5 of every project executed at GE reduced its potential cost overrun as a result of a structured thought process that is based exclusively on what the "does" not what it is been followed (Gokharn 1998, Dutta 2002 & Harish and Menezes 2011). Vast studies have been conducted on value engineering and the findings show that it "*is a powerful problem-solving tool that can reduce costs while maintaining or improving performance and quality requirements".* The ability of this process to reduce cost in the offshore drilling operations is not in doubt as evidence from Kelly & Male (1993), David (2005), Olawuyi (2009), and Arumugam & Ramareddy (2012) supports the recommendations of the experts that decisions on optimal expenditure of funds and required function and quality level of projects can be made using value engineering. Moreover, companies stand to gain in several ways if value engineering process is successfully implemented due to its ability to identify opportunities to remove unnecessary costs while assuring quality, reliability, performance, and other critical factors that meet or exceed customer's expectation.

Additionally, more experiences were shed by the 16 experts on how waste has been cut and improvements in operational efficiency has been achieved as a result of value engineering techniques. On average, it was revealed that value engineering can help reduce 5-10% of project cost if a systematic approach is implemented to keep the waste problem in business to the minimum. The researcher is of the firm believe that lean thinking and improvement in operational standards in the offshore drilling industry can help deliver projects on time and reduce cost. The experts' argued that it is necessary to always have ***"effective plan should be put in place"*** since ***"cost is a living element and must be properly incorporated into costing systems".*** It is therefore not implausible relying on the observations to suggest that, the use of value engineering in the oil industry has the ability to identify the cost and causes of waste, and can help make process improvements which are effective long-term and has the potential to reduce the overall operations cost of projects.

9.3 Contracts and negotiations

In the oil and gas industry, one of the steps to reducing cost is by putting up strong negotiation and cost effective contracts. About 80% of the experts interviewed were of the view that all contracts and negotiations teams during BID process should be made of project delivery experts. This is important because having such members in the team help in guiding the BID process towards agreeing on an amount that is realistic for the project execution. It is equally necessary as evidence shared by the experts interviewed revealed that more often than not it is senior management and technical people who most often do not have project delivery experience are the ones normally selected by companies to form the BID team which usually results in underestimation of the project time and cost schedules. It is logical to conclude that managers for any project should have a say or contribute to the pricing of projects as this will help in arriving at a project cost that is close to accurate. The researcher supports the idea of having experienced and strong team in place for contracts negotiations on projects as this can inform decisions such as the need to look for new suppliers, finding alternative materials etc. based on lessons learned from previous projects is critical in reducing projects cost.

It has been observed and was submitted by the experts that having project delivery members around during contracts negotiations and bidding process helps to identify the *"right contractors, service producers, suppliers, and quality of resources which help to reduce cost"*. An example of cost savings of $150million made by NNPC of Nigeria in 2013 was through a renegotiation done with Shell plc using project managers who had experience in the operations of the Erha offshore fields was cited as evidence to support this point which confirms the relevance of this discussion. Other critical issues raised towards reducing cost in offshore drilling operations is having a clearly defined plan for every project negotiation. Evidence has shown that if comprehensive cost benefit analysis of a project is done it helps in the negotiating process. It was posited that "*having a well thought through plan that highlights what the operator wants, identifying the weaknesses and strengths of the company and anticipating all options always lead to a win-win situation in contracts negotiations*".

Furthermore, the legal battle between BP and Transocean that ensued after the Macondo oil spill in 2008 has provided valuable lessons to oil companies as to how cost and liabilities can be reduced if a well thought through contracts is signed. The cost in the region of more than $20billion incurred by BP and its partners could have been reduced if the contract covered very of their operations including their process as the accident was a procedural error (UK House of Commons 2011, BP 2012 & Schlumberger 2015). The 31 experts used for this research acknowledged that the type of contracts signed, liabilities, settlement and disputes packages agreed ca help to reduce cost. Again, health and safety issues and others drilling factors if apportioned to each party during contract negotiations can also help to reduce project cost overrun in the upstream drilling sector.

9.4 Cost sensitization and education

Another important factor that was recommended by all the experts as critical to reducing cost in deep water offshore drilling operations was cost sensitization and training. When issues of cost reduction are handled inter-departmentally or throughout the project life cycle it creates the awareness and consciousness among all workers. If the drilling engineer is conscious of the fact that a bag of cement wasted during casing has a cost implication it places the responsibility on all to cut waste and remain efficient which consequently reduces project costs. Past experiences shared by the experts showed a positive attitude among workers at work which reflected in cost reductions in operations when *"every project team member or stakeholder is sensitized or educated on the need for cost reduction by raising issues such as ..What project reduction is? What are the impacts of cost overrun?-e.g. its effects on next project, investments, profit, bonuses etc. and highlighting the factors and indicators to look at can help*". When the problem of reducing cost becomes not only the problem of project accountants or project managers but everyone else's problem, then there exists a high probability of success.

Again, cost reduction education is very important in terms of managing project cost especially in Africa this is because *"though there are a lot of people who are technically gifted but lacking in project management skills set needed to delivering project on time, within budget and with adequate quality which many at times make the projects overrun their budgets".* From the literature, it was demonstrated that politics and other economic factors do contribute to project cost overrun. Though such factors are externalities knowledge of them by project team members help to not only be realistic in terms of deciding on project timescales and cost but helps to reduce unplanned cost and unnecessary surprises. The call for cost sensitization and education cannot be trivialised as findings from the work of Savage (1971), Sawczuk (1996), Salazar (2010), & Yost *et al.* (2015) have proven that education is one of the best ways to tackle cost overrun as close to 80% of project overruns is caused by human errors and as such educating the "perpetrators" is in part solving the problem. Aside from that, constant education on new processes and techniques usually provide businesses opportunities to improve in all sectors which subsequently leads to efficiency and cost reduction.

Additionally, it would be difficult for employees' attitude to change overnight if they are not made aware of how they contribute to cost overrun and the need to address it. Hence, the cost reduction training could be broken down by analysing the overall cost overrun of the company either yearly or monthly and breaking it down to the contribution departments make to that and if possible to individual levels for learning purposes. Departments could be tasked to determine how they can contribute towards achieving cost reduction for the company. This will not only inform but place a sense of responsibilities on every employee to help make things better. The researcher agrees with the experts interviewed that there is a higher possibility to have cost reduced in projects "*if everyone involves in a project is conscious of the cost consequences of their actions companies stand a chance to save millions in cost in the oil and gas industry*".

9.5 Budgetary control

In addition to the above points discussed, another way to reduce cost is by putting in place budgetary or cost control mechanism or process in place. This is extremely useful as it will assist and direct anyone involved in the project in terms of planning, coordinating and controlling the activities of the project. To fully benefit from the process, it is imperative that upper and lower limit cost is set for each of the activity for the project to help in monitoring, evaluation, and appraisal. This suggestion is consistent with best budgetary standard practices recommended by IMF and World Bank in their yearly fiscal transparency documents which add to the relevance of this process. Particularly, when financial control measures are put in place at project commitment stage, delivery, before payment and after payment audit help not only to reduce cost but offer valuable lessons for process improvements in future projects. Again, some of the experts' interview confirmed that in projects where there existed strict budgetary controls, *"we always endeavoured to operate within our means and delivered*". This account then suggests that tight financial controls would not only reduce cost but force workers to be efficient and responsible.

Moreover, budgetary control can boost team work and improve communication and coordination among staffs. This is because since every project team has an allocated fund it motivates the team members to help one another in order to save cost and meet project deadlines, and cost targets. Again, experiences shared by experts showed that workers become more conscious of how their performance can impact the overall goal of the company which helps in any cost reduction strategy. Enforcing this during every project in the deepwater offshore drilling industry in sub-Saharan Africa has the potential to save millions as this will reduce negligence and waste which are common phenomenon during project deliveries. Emphasis on low tolerance for deviations (over spending), detailed project activity follow ups, and intense discussions of project performance against planned cost regularly are very useful in achieving this. It can be argued that if the aforementioned steps are not in place, cost reduction becomes mechanistic lacking the responsive actions that are to some degree a self-governing action needed to enforce the control.

Furthermore, as discussed in the literature, the best way to set budgetary control is to understand the factors or variables that usually overrun their budgets. The improved elicitation process developed can be used to find out which factor/s should be controlled as failure to identify the critical cost factors may not help the business to achieve its intended purpose. With a clear understanding of what needs to be controlled cost wise, it then can inform proper allocation and usage of resources. "*Doing so will ensure that you're fully utilizing the resources you have and that you have the right resources ready for the rest of the project*". Additionally, as discussed in the literature review, scope changes can also cause project overruns and therefore to reduce the occurrence of this and its consequent costs, project managers must be aware of any potential scope changes and unplanned work so that the necessary billable hours and added to the budgetary control process.

9.6 Cost and time optimization techniques

It was established in the literature reviewed in chapters 1, 2 and 3 that drilling time has a direct correlation with cost. Considering that and delays, currency depreciation and politics which has been comprehensively discussed and analysed in this research are all associated with time and contribute to cost overrun. Hence to reduce cost, one of the effective techniques to use is to optimize project time and cost to achieve the greatest benefit. Meeting project time and cost should be made a compulsory criterion for success of project delivery (Rahman 2010, and Mohd 2010). This will ensure issues such as poor site management and supervision, financial difficulties, inadequate contractor experience, incorrect planning and scheduling and several other factors discussed in the literature can be properly addressed. One of the standards of cost optimization is to find an "*alternative with the most cost effective or highest achievable performance*" and as such reviewing the understanding and review of cost overrun causes are critical to cost reduction. This research has contributed to knowledge by not only identifying cost overrun causes and their independent effects on overall project cost. But also a Bayesian elicitation framework has been developed which can be used to identify several other cost factors in future oil and gas projects

Again, projects in the sub-Saharan Africa and in many parts of Africa are more often saddled with poor project cost management. Usually, the goal and motivation of drilling team members are to get the project completed irrespective of how much time and cost it may demand which is why the problem of cost overrun persists. As part of the findings and contribution of this research, it is important to demand cost management strategy and process from contractors and project managers before a project take off to ensure that well thought through plans and commitments are made to deliver the project in the most cost effective way. A cost management plan/process can help in cost monitoring and cost control systems of a project which can raise early cost alarm for actions to be taken on any parameter that has the potential to overrun its allocated cost. The researcher found tools such as Gantt chart, network analysis, Critical Path Method (CPM) and Programme Evaluation Review Technique (PERT) to be useful in evaluating project cost performance and indicating factors that can help to reduce the project cost.

Another way to reduce project cost is by optimizing operations technology in projects. Section 2.3.2 and 2.3.3 demonstrated that type of drill bits, casing scheme, mud technology and cement logging used in drilling has an influence on the time and cost of the project (Tibbits *et al.* 2002, Kaiser 2009, and Osmundsen *et al.* 2010). Therefore finding the right technology to use in deepwater offshore drilling can reduce cost which is why the researcher recommends continuous review and comparisons of drilling technologies every project and to the industry standards to ensure at all times the most cost effective technology is used in delivering projects. There is evidence from literature and from the experts interviewed that, consist reliance on low technologies or traditional drilling methods delay projects unnecessarily and cause cost overrun. It is therefore imperative that effective strategies and technologies are employed always in offshore drilling if cost reduction targets are to be achieved.

Moreover, to achieve time and cost optimization and consequently to reduce project cost, several analytical methods can be used. The researcher suggests the use of Excel to establish the feasibility of proposed project solutions based on its known constraints. This can help to generate several scenarios which would inform the project team on different risks and benefit and to develop the most appropriate plan and strategy to deliver a project. Also, sensitivity analysis and Net Present Value (NPV) can be employed in offshore project delivery as means to determine where and when cost reductions can be made.

9.7 Chapter Summary

To reduce the cost of projects in the deepwater offshore drilling industry in the sub-Saharan Africa, it is critical to meet the modern project requirements by estimating projects time, cost and resources with reasonable accuracy. It was argued in this chapter that the use of value engineering can help to reduce waste and increase efficiency in offshore operations. Also, rigorous contract negotiations that have project delivery team members during bidding up to project completion is essential if project cost is to be reduced. Educating and sensitizing stakeholder of a project on the need to reduce cost is one of the ways to addressing cost overrun. Finally, cost and time optimization was argued to be also equally vital in meeting operations efficiency and cost reduction targets. The next chapter presents the research conclusion, the summary of project contributions and recommended future work.

Chapter ten

CONCLUSION, CONTRIBUTION, AND FUTURE WORK

10.1 Conclusion

This section concludes the research by summarising the activities undertaken to accomplish the research objectives and questions discussed in sections 1.3 and 1.5 respectively. The development of an integrated Bayesian and ABC cost estimation model, which demonstrates the ability to generate a more accurate cost estimates than the existing cost models and reduce cost overrun in Sub-Sahara Africa region, has met the main aim of the research. It was demonstrated in chapter 2, that external factors to offshore deepwater drilling such as politics, delays, and depreciation of currency against the UDS are some of the critical cost overrun drivers in sub-Sahara Africa operations.

Furthermore, modelling requirements for cost model in the oil industry was examined in chapter 3 whereas a review of the past performances of existing cost models in the Sub-Sahara Africa offshore drilling industry in chapter 4 revealed the need for a validated cost estimation framework that can give accurate estimations with limited data, and factor probability results of all the cost drivers in the offshore deep-water drilling operations into a model. The scarcity of a comprehensive model that is both suitable and applicable to the systems and operations of the industry and therefore justified the choice of the model developed in the study. Hence the model developed in this study which involved combining the results of a probability algorithm using the Bayes rule to calculate probabilities of experts and a linear equation for the ABC was considered appropriate to handle the aforementioned challenge. Chapter 5 analysed the current elicitation process and developed a more improved elicitation process which has been tested and verified using both pilot study and for the collection of primary data for the main study which is captured in chapter 6.

In assessing the performance of the developed model, results of the model was compared with the estimates of the existing (old) models using data from 3 offshore fields from 3 different countries. Results from Luanda offshore field in Angola showed a reduction of cost overrun from 34.09% to 24.55% using the newly developed model. Again the model reduced cost overrun of the Jubilee field in Ghana from 32.94% to 22.88%, while Erha field in Nigeria was reduced to 21.30% from an existing average cost overrun of 32.20% within the period of 2005 to 2015. The results suggest that combining Bayesian and the ABC cost estimation techniques justify the appropriateness of the approach used to address the research questions raised in this study. Although comparison of these results demonstrate that the differences in the results could be attributed to the uniqueness of each country in terms of how cost drivers affect operations nonetheless, the new model demonstrated remarkable ability in reducing cost overrun in the offshore drilling industry. Hence, the identification of the cost overrun causes, demonstration of the need for a more robust cost estimation model, and the development of a new cost estimation model that is applicable to the offshore deepwater drilling industry has completely achieved the aim and objectives and answered all the research questions set for the study.

These results imply that oil operations are required to critically examine how much cost they allocate for the cost drivers discussed above as failure to do so could escalate cost overrun further and affect future oil discovery and development especially. This statement is truer considering the rapid decline of global oil price from an average of $100USD from 2008-mid 2014 and the current average of below $50USD from mid-2014 to Jan 2016 (Bloomberg 2016). The expert judgment used for the Bayesian analysis was cross analysed with previous findings in the wider literature and was found to be reliable and credible which guarantees the validity of the research findings.

Again, as discussed in section 5.3 on the improved elicitation process developed, provision of training before elicitation, and a well-structured questionnaires and elicitation process can reduce any possible heuristics and biases from the point of view of estimators or investigators. However, one limitation of the model is its inability to detect biased responses that can lead to erroneous results as is in the case of expert judgment based models but can be managed through using preselection questionnaires, structured questions and briefing before elicitation as proposed in chapter 5 of the study.

10.2 Contribution to knowledge

The current practice and state of art in offshore drilling cost estimation showed poor coverage of known unknown factors (critical factors) which are the cost drivers of every drilling project. Therefore, the novelty and contribution of knowledge are gained through:

- ✓ the modelling of the critical factors (known unknowns) of offshore deepwater drilling cost overrun using Bayesian Network techniques and integrating the model with Activity Based Costing (ABC) estimation method to improve cost estimation. Findings from the study revealed that the combination of Bayesian Network approach and ABC provided a more robust and interactive cost estimation system for the offshore drilling industry.
- ✓ the development of an improved elicitation process and guidelines which were tested, verified and used in 2 pilot studies and in

gathering primary data for the model developed is a major contribution to this study.

- ✓ the demonstration that formalizing expert judgment in offshore project cost estimation produces better cost estimates compared to the traditional (arbitrary) method of elicitation and as an approach that cannot be overlooked in cost estimation models if cost overrun is to be eliminated or reduced in the offshore deepwater drilling industry.
- ✓ an analysis of cost reduction techniques backed by evidence and qualitative data was presented to ensure the further usefulness of this study to the oil industry which also added to the knowledge contributed by this research

10.3 Future work

To expand the significance of this research to several industries and projects, future research into these topics listed below have been identified and recommended

- ✓ Identify other gaps still existing between the actual cost of projects and the new model developed by the researcher.
- ✓ The development of a standardized method for ranking expert judgments. This system should be able to match the views expressed by experts with a probability number/figure specified in the standard which can be used to calculate the joint probability. This will reduce or eliminate biases and increase the credibility of results as the role of the experts would only be to elicit their views while the elicitation facilitator matches those comments with the correct standard

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Appendix

Appendix A-1: Primary cost of drilling cost factors for Luanda offshore field

The table contains cost of the 5 cost factors for offshore drilling in Luanda fields Angola from 2005-2015. This data was used to develop the ABC equation in section 7.2.1 above.

Year	**No Wells**	**Services**	**Rigs**	**Logistics**	**Eq&Mat**	**Admin**	**Total**
2005	9	20.09	19.52	8.04	5.74	4.01	57.40
2006	7	17.85	17.34	7.14	5.10	3.57	51.00
2007	8	36.89	35.84	14.76	10.54	7.37	105.40
2008	12	77.32	75.11	30.93	22.09	15.45	220.90
2009	7	88.62	86.08	35.45	25.32	17.73	253.20
2010	5	24.08	23.40	9.63	6.88	4.81	68.80
2011	11	36.82	35.77	14.73	10.52	7.36	105.20
2012	8	65.07	63.21	26.03	18.59	13.00	185.90
2013	10	84.60	82.18	33.84	24.17	16.91	241.70
2014	2	10.03	9.74	4.01	2.87	2.00	28.65
2015	1	4.20	4.10	1.70	1.20	0.80	12.00
Total	**80**	**465.57**	**452.29**	**186.26**	**133.02**	**93.01**	**1330.15**
per well	**1**	**5.82**	**5.65**	**2.33**	**1.66**	**1.17**	**16.63**

Source (IEA 2014, ExxonMobil 2003-2014, IHS 2015, and Rigzone 2015

Appendix A-2: Primary cost of drilling cost factors for Jubilee offshore field

The table contains cost of the 5 cost factors for offshore drilling in Jubilee offshore fields Ghana from 2005-2015. This data was used to develop the ABC equation in section 7.2.2 above.

Year	**No Wells**	**Services**	**Rigs**	**Logistics**	**Eq&Mat**	**Admin**	**Estimate**
2005	7	26.25	25.50	10.50	7.50	5.25	75.00
2006	6	25.31	24.58	10.12	7.23	5.06	72.30
2007	4	18.83	18.30	7.53	5.38	3.76	53.80
2008	7	34.72	33.73	13.89	9.92	6.94	99.20
2009	6	35.00	34.00	14.00	10.00	7.00	100.00
2010	5	26.36	25.60	10.54	7.53	5.27	75.30
2011	18	71.23	69.19	28.49	20.35	14.24	203.50
2012	14	73.50	71.40	29.40	21.00	14.70	210.00
2013	8	26.88	26.11	10.75	7.68	5.38	76.80
2014	2	7.45	7.24	3.00	2.13	1.48	21.30
2015	3	10.39	10.10	4.16	2.97	2.08	29.70
Total	**80**	**355.92**	**345.75**	**142.38**	**101.69**	**71.16**	**1016.90**
per well	**1**	**4.45**	**4.32**	**1.78**	**1.27**	**0.89**	**12.71**

Source (IEA 2014, Tullow 2003-2014, IHS 2015, and Rigzone 2015)

Appendix A-3: Primary cost of drilling cost factors for Erha offshore field

The table contains cost of the 5 cost factors for offshore drilling in Erha offshore fields Nigeria from 2005-2015. This data was used to develop the ABC equation in section 7.2.3 above.

Year	**No Wells**	**Services**	**Rigs**	**Logistics**	**Eq&Mat**	**Admin**	**Estimate**
2005	6	28.63	27.81	11.45	8.18	5.73	81.80
2006	8	37.38	36.31	14.95	10.68	7.48	106.80
2007	8	42.77	41.53	17.11	12.22	8.57	122.20
2008	9	53.13	51.61	21.25	15.18	10.63	151.80
2009	11	55.69	54.09	22.27	15.91	11.14	159.10
2010	9	39.09	37.98	15.64	11.17	7.82	111.70
2011	8	50.36	48.93	20.45	14.39	9.77	143.90
2012	8	42.00	40.80	16.80	12.00	8.40	120.00
2013	10	42.21	41.00	16.88	12.06	845.00	120.60
2014	2	10.54	10.23	4.12	3.01	2.20	30.10
2015	1	4.02	3.91	1.61	1.15	0.81	11.50
Total	**80**	**405.82**	**394.20**	**162.53**	**115.95**	**917.55**	**1159.50**
per well	**1**	**5.07**	**4.92**	**2.03**	**1.45**	**1.03**	**14.50**

(IEA 2014, Shell 2003-2014, IHS 2015, and Rigzone 2015

Appendix A-4: Expert probabilities for Delays from Ghana, Angola and Nigeria

Individual Probabilities on Delays by Experts (in %)												
Ref	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**Average**
G001	30	40	35	30	35	30	35	45	40	40	35	35
G002	40	35	40	30	30	40	30	40	35	30	45	35
G003	20	30	20	25	35	45	25	30	40	30	25	40
G004	30	20	20	35	20	30	25	25	25	20	20	40
G005	20	20	25	20	30	25	30	20	25	35	20	25
G006	30	20	20	25	30	25	20	30	20	30	25	25
G007	30	20	30	25	35	30	25	30	35	40	30	30
G008	35	40	35	45	30	30	40	35	40	25	35	35
G009	20	20	25	20	30	30	25	25	40	35	35	30
G010	40	35	40	45	40	40	45	40	35	40	35	40
G011	30	25	20	20	25	25	30	20	35	30	40	30
G012	40	40	30	40	30	40	35	40	30	30	30	35
G013	35	30	40	40	35	25	45	30	35	30	30	35
G014	20	30	20	25	35	45	25	30	40	30	25	30
G015	25	20	25	20	25	20	35	20	30	35	20	25
Gh Avg	**33**	**32**	**32**	**34**	**33**	**32**	**35**	**33**	**34**	**33**	**32**	**33**
N001	35	30	20	30	40	25	30	35	20	30	20	30
N002	20	20	30	25	20	25	30	25	25	30	20	25
N003	10	15	15	15	10	15	20	10	20	20	15	15
N004	40	40	45	50	45	45	45	50	40	55	40	45
N005	20	20	20	20	20	20	20	20	25	25	15	20
N006	15	20	25	25	15	20	25	20	15	15	20	20
N007	20	30	20	25	35	45	25	30	40	30	25	30
N008	30	45	35	30	40	30	20	25	30	35	30	35
N009	30	25	20	40	40	40	45	30	35	35	40	35

N010	20	25	25	30	25	30	20	30	25	20	20	2
N011	25	20	25	30	30	40	30	35	35	30	35	30
Nig Avg	**23**	**26**	**25**	**28**	**27**	**28**	**26**	**27**	**27**	**28**	**25**	**26**
A001	25	20	15	20	20	20	20	20	20	20	20	20
A002	20	20	20	20	20	20	20	20	20	25	15	20
A003	30	20	20	35	20	30	25	25	25	20	20	25
A004	20	30	20	25	35	45	25	30	40	30	25	30
A005	30	20	25	30	20	30	25	30	20	20	20	25
A006	20	30	20	25	35	45	25	30	40	30	25	30
A007	30	25	25	35	30	30	35	30	35	35	20	30
Ang Avg	**25**	**24**	**21**	**27**	**26**	**31**	**25**	**26**	**29**	**26**	**21**	**25**

Appendix A-5 : Expert probabilities for Politics from Ghana, Angola and Nigeria

Individual Probabilities on Politics by Experts (in %)											
Ref	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**Average**
G001	25	35	30	30	25	25	30	35	30	35	30	30
G002	40	50	45	25	30	40	35	30	45	40	35	35
G003	30	20	25	30	20	30	25	30	20	20	20	25
G004	30	25	35	30	30	25	35	25	30	30	30	30
G005	40	45	50	35	40	35	40	45	35	50	45	45
G006	25	30	30	30	25	35	30	35	30	30	25	30
G007	45	40	45	30	35	35	30	35	40	35	40	35
G008	40	35	40	50	45	35	45	40	30	35	40	40
G009	15	20	20	25	20	20	20	25	20	20	15	20
G010	20	25	20	20	20	15	20	20	20	15	20	20
G011	45	40	45	35	45	45	40	35	30	40	45	40
G012	35	55	40	30	30	40	30	45	30	45	30	35
G013	25	25	20	30	25	30	20	30	25	20	20	25
G014	30	25	25	35	30	30	35	30	35	35	20	30
G015	40	50	45	40	40	30	45	35	40	45	40	45
Gh Avg	**32**	**34**	**33**	**32**	**31**	**30**	**32**	**33**	**31**	**33**	**30**	**32**
N001	40	45	40	40	45	30	50	40	35	30	40	40
N002	50	40	40	40	45	30	45	35	40	55	40	45
N003	55	45	55	45	50	55	50	45	50	50	45	50
N004	40	40	35	45	50	40	40	45	30	35	40	40
N005	45	40	45	40	35	40	40	40	40	40	50	45
N006	70	65	55	60	55	55	65	60	55	65	55	60
N007	35	40	40	45	40	45	40	40	35	40	30	40
N008	35	40	55	35	40	35	40	45	35	45	45	45
N009	45	40	45	40	40	40	45	30	35	35	40	40
N010	50	55	60	55	60	55	50	50	55	55	50	55
N011	55	50	50	45	50	50	55	45	50	50	50	50
Nig Avg	**48**	**46**	**48**	**46**	**47**	**44**	**48**	**44**	**43**	**46**	**45**	**46**
A001	40	35	40	45	30	40	45	30	25	25	30	35
A002	35	40	45	45	40	40	40	45	35	40	35	40
A003	45	30	35	55	45	35	50	35	40	35	40	40
A004	20	30	20	25	35	45	25	30	40	30	25	30
A005	50	40	40	40	45	30	45	35	40	55	40	45
A006	25	30	35	40	35	30	35	30	25	20	25	30
A007	30	45	40	45	50	45	30	45	30	40	35	40

Ang Avg	**35**	**37**	**37**	**42**	**40**	**38**	**39**	**36**	**34**	**35**	**33**	**37**

Appendix A-6: Expert probabilities for Currency from Ghana, Angola and Nigeria

Individual Probabilities on Currency by Experts (%)											
Ref	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**Average**
G001	45	25	35	40	40	45	35	20	30	25	35	35
G002	20	15	15	45	40	20	35	30	20	30	20	40
G003	50	50	55	45	45	25	50	40	35	50	55	35
G004	40	55	45	35	50	45	30	50	45	50	50	30
G005	40	35	25	45	30	40	30	35	40	15	35	30
G006	45	50	50	45	45	40	45	35	35	30	45	45
G007	25	30	25	45	30	35	45	35	25	25	30	35
G008	25	25	25	05	25	35	15	25	30	40	25	35
G009	65	60	55	55	50	50	55	50	50	45	45	50
G010	40	40	40	35	40	45	35	40	40	55	45	40
G011	25	35	35	45	30	30	30	45	35	30	15	30
G012	25	05	30	30	40	20	35	15	40	25	40	30
G013	40	45	50	30	40	45	35	40	40	50	50	40
G014	50	45	55	40	35	25	40	40	25	35	55	40
G015	35	30	30	40	35	50	20	45	30	20	40	30
Gh Avg	**50**	**49**	**50**	**51**	**50**	**48**	**47**	**48**	**46**	**47**	**51**	**35**
N001	25	25	40	30	15	45	20	25	45	40	40	30
N002	30	40	30	35	35	45	25	40	35	15	40	30
N003	35	40	30	40	40	30	30	45	30	30	40	35
N004	20	20	20	05	05	15	15	05	30	10	20	15
N005	35	40	35	40	45	40	40	40	35	35	35	35
N006	15	15	20	15	30	25	10	20	30	20	25	20
N007	45	30	40	30	25	10	35	30	25	30	45	30
N008	35	15	10	35	20	35	40	30	35	20	25	20
N009	25	35	35	20	20	20	10	40	30	30	20	25
N010	30	20	15	15	15	15	30	20	20	25	30	20
N011	20	30	25	25	20	10	25	20	15	20	15	20
Nig Avg	**29**	**28**	**27**	**26**	**26**	**28**	**25**	**29**	**30**	**26**	**30**	**28**
A001	35	45	45	35	50	40	35	50	55	55	50	45
A002	45	40	35	35	40	40	40	35	45	35	50	40
A003	25	50	45	10	35	35	25	40	35	45	40	35
A004	60	40	60	50	30	10	50	40	20	40	50	40
A005	20	40	35	30	25	40	30	25	40	25	40	30
A006	55	40	45	35	30	25	40	40	35	50	50	40
A007	40	30	35	20	20	25	35	25	35	25	45	40
Ang Avg	**41**	**42**	**42**	**31**	**33**	**31**	**37**	**37**	**39**	**40**	**46**	**38**

Appendix A-7: Joint Probabilities for the sub-Saharan Africa- by experts

Joint Probabilities for the sub-Saharan Africa- by experts			
Year	**Politics**	**Delays**	**Currency**
2005	40	20	40
2006	35	30	35
2007	38	30	32
2008	40	30	30
2009	38	33	29
2010	35	31	34
2011	38	37	25
2012	32	32	36
2013	33	31	36
2014	34	34	32
2015	29	29	42
Average	35	35	30

Appendix A-8-Joint probability of the input-output results

The Input output probability results is calculated by finding the conditional and unconditional probabilities of the three variables using equation (6.5) below

P(A,B,C)=[P(A/B,C)P(C/B)P(B)]*[P(B/C,A)P(A/C)P(C)]*[P(C/A,B) P(B/A)P(A)]

Event	**Probability**
P(A/B,C)	0.99
P(C/B)	0.90
P(B)	0.35
P(B/C,A)	0.99
P(A/C)	0.95
P(C)	0.30
P(C/A,B)	0.99
P(B/A)	0.95
P(A)	0.35

Hence P(A,B,C)=[0.99*0.90*0.35]*[0.99*0.95*0.30]*[0.99*0.95*0.35]

=[0.32]*[0.28]*[0.33]

=0.295 or 29.50%

Appendix A-9-Joint probability results for Luanda offshore

The probability results for Luanda offshore for each of the probability event in the table is calculated by finding the conditional and unconditional probabilities of the three variables using equation (6.5) below

P(A,B,C)=[P(A/B,C)P(C/B)P(B)]+[P(B/C,A)P(A/C)P(C)]+[P(C/A,B) P(B/A)P(A)]

Event	**Probability**
P(A/B,C)	0.90
P(C/B)	0.95
P(B)	0.37
P(B/C,A)	0.99
P(A/C)	0.90
P(C)	0.38
P(C/A,B)	0.99
P(B/A)	0.95
P(A)	0.25

Hence P(A,B,C)=[0.90*0.95*0.37]*[0.99*0.90*0.38]*[0.99*0.95*0.25]

=[0.3164]*[0.3386]+[0.2351]

=0.2519or 25.19%

Appendix A-10 Joint probability results for Jubilee offshore

The probability results for Jubilee offshore for each of the probability event in the table is calculated by finding the conditional and unconditional probabilities of the three variables using equation (6.5) below

$$P(A,B,C)=[P(A/B,C)P(C/B)P(B)]+[P(B/C,A)P(A/C)P(C)]+[P(C/A,B)\ P(B/A)P(A)]$$

Event	**Probability**
P(A/B,C)	0.90
P(C/B)	0.95
P(B)	0.33
P(B/C,A)	0.95
P(A/C)	0.99
P(C)	0.35
P(C/A,B)	0.85
P(B/A)	0.90
P(A)	0.32

$$\begin{aligned} P(A,B,C) &= [0.90*0.95*0.33]*[0.95*0.99*0.35]*[0.85*0.90*0.32] \\ &= [0.2822]*[0.3292]*[0.2678] \\ &= 0.2488 \text{ or } 24.88\% \end{aligned}$$

Appendix A-11 Joint probability results for Erha offshore

With the average probability of 43% for politics, 35% for delays and 32% for depreciation of the Naira against the USD as presented in table 7-5 above, the probability results for Erha offshore for each of the probability event in the table is calculated by finding the conditional and unconditional probabilities of the three variables using equation (6.5) below

P(A,B,C)=[P(A/B,C)P(C/B)P(B)]*[P(B/C,A)P(A/C)P(C)]*[P(C/A,B) P(B/A)P(A)]

Event	**Probability**
P(A/B,C)	0.95
P(C/B)	0.90
P(B)	0.26
P(B/C,A)	0.99
P(A/C)	0.95
P(C)	0.28
P(C/A,B)	0.95
P(B/A)	0.90
P(A)	0.46

P(A,B,C)=[0.95*0.90*0.26]*[0.99*0.95*0.28]*[0.95*0.90*0.46]

=[0.2223]*[0.2633]*[0.3933]

=0.2302 or 23.02%