INVESTMENT DECISION AND RISK ANALYSIS IN OIL EXPLORATION PROJECTS - A MONTE CARLO VALUE-AT-RISK (VaR) APPROACH

By

Abdul Adamu[1]

Abstract

This study examines the application of Monte Carlo simulation Value-at-Risk (VaR) technique for risk analysis and investment decision in oil exploration project. The study uses the historical daily crude oil future price from Energy Information Administration and a hypothetical Okoro oilfield in Niger Delta – Nigeria. The analysis of the data was done using Value @ Risk Monte Carlo simulation and the finding shows that the project is profitable because it has a positive NPV. It was recommended that the company should undertake the oil exploration as the chances of a positive return on investment are high.

Keywords: ***Monte Carlo simulation, Value-at-Risk (VaR), Oil exploration, NPV.***

Introduction

Major changes are occurring in the oil and gas industry. The old model of vertically-integrated organizations and monopolistic energy businesses is breaking up and being replaced by competition and privatization (Keppler, 2007). Participants in competitive markets are expected to make better investment decisions because they bear the risk of their decisions (Serletis and Bianchi, 2007). Making investment decision in the oil and gas industry involves having to make long term forecasts of projected cash flows. Adequate knowledge of technical parameters – capital requirements and operating cost, commodity prices and other economic and financial variables – must be gathered using an implicit model of how petroleum and financial markets work.

Energy companies operate in a very competitive business environment, which means that accurate and timely decisions must be made based on the evaluation of available information. As a result of this competitive nature of the business, decentralization of decision-making became essential for many energy operations (Chevalier, 2007). Since the energy market is a major recipient of investment funds, financial analysis of investment is an essential requirement. The capital intensive nature of energy supply requirements as well as the high degree of asset specificity of fossil fuel extractive industry makes assets vulnerable to risk and call for investment decision to be made well in advance to meet operation deadlines. In addition, variations in oil prices makes investment in oil exploration highly risky. Corporate investors assessing new oil exploration opportunities have difficulty judging whether current prices indicate long-term economic values or may lead to financial losses. Consequently, this requires a potent tool for risk quantification and management.

Risk management denotes a set of activities and tools used for assessing, evaluating and measuring a corporation's exposure to various risks within her portfolio of assets and managing it using financial instruments, insurance and other types of contracts. The value of energy trades can change over time as market conditions and underlying price variables change. A price forecast is the foundation for determining a firm's risk in managing their energy supply and their forward contracts for energy trades. In energy markets, proper risk management depends not only upon proper portfolio analysis tools but also on a solid foundation of forward price.

Petroleum exploration deals with many unknowns, with high risk and uncertainty being an inherent part of the oil and gas industry. The management of risk in oil and gas exploration has always been a difficult subject, and it is even more important in these days of high capital investment and high volatility of oil price. Within the oil markets, Value at Risk (VaR) has become an essential tool to this end. Mehdi and Saeed (2006) assert that VaR can be used to quantify the maximum oil price changes associated with a likelihood level which constitutes a fundamental point when designing risk management strategies.

The main objective of this study is to present an application of the Monte Carlo simulation based VaR techniques about the investment projects selection. Specifically, the study examine the role that Monte Carlo simulation VaR technique can play in managing oil exploration risks as affected by fluctuation in oil prices, output, CAPEX, operating cost and cost of capital. It is wish to present a comprehensive and simple method, that is to say, easy to apply by the decision makers in the petroleum companies. Premium evaluation criteria in investment are necessary in each step of the decision, however, the important question that needs to be answer in this research is: how shall we use the VaR optimization approach to make the strategic investment decision as easy as possible from a practical point of view? Thus, this work assumed that the company is considering an exploration project and it is exposed to both exploration (quantity) and price risks.

Literature Review

VaR is defined as the maximum expected loss in the value of an asset or a portfolio of assets over a target horizon, subject to a specified confidence level. Thus, VaR sums up the risk which an asset or a portfolio is exposed to in a single monetary (or expected return) figure. That makes the VaR approach directly applicable to the field of energy prices. Statistically speaking, the calculation of VaR requires the estimation of the quintiles of the distribution of returns and can be applied to both the left (long positions) and the right (short positions) tails.

As far as the energy markets are concerned, there has been a recent increase in the relevant empirical literature on testing VaR models and assessing their performance. These papers include a wide range of models from the standard Variance Covariance, to Historical Simulation variations, Monte Carlo simulation, and a plethora of models of the ARCH-type, also including long memory variations, under different distributional assumptions for the returns' innovation (see among others, Chiu, Chuang & Lai, 2010; Aloui & Mabrouk, 2010; Huang, Lee & Liu, 2008; Sadeghi & Shavvalpour, 2006; Giot & Laurent, 2003; Cabedo & Moya, 2003). Moreover, there have also been a few studies estimating VaR on the energy markets using an extreme value theory approach (see among others, Nomikos & Pouliasis, 2011; Marimoutou, Raggard & Trabelsi, 2009; Krehbiel & Adkins, 2005). Results however, are contradictory in terms of the accuracy of the VaR models proposed, with plenty of discussions focusing on as to whether the simpler models can outperform the more complex/flexible ones. Brooks and Persand (2003) find that simple models achieve comparably better VaR forecasts to the more complex ones, while Mittnik and Paolella (2000) show that more accurate VaR forecasts can be achieved with the more flexible models. In addition, Bams, Lehnert and Wolff (2005) find that amongst the models they examine, the simple models often lead to underestimation of the VaR, whereas the opposite holds for the more complex models that seem to lead to overestimation of the VaR.

Furthermore, following the emerging concept in the literature of combining VaR forecasts, Chiu at al. (2010) propose a composite VaR model to increase forecast effectiveness. In the same lines, Hibon and Evgeniou (2005) suggest that by combining forecasts instead of selecting an individual forecasting model, modelling risk is reduced. Choosing the most suitable VaR model for each commodity is of utmost importance for all energy market players, traders, hedgers, regulators, and policy-makers as modelling risk is reduced, and thus avoiding faulty risk management caused by the selected model's inefficiencies.

In principle, there are three general approaches to compute VaR, each one with numerous variations. The first one is to assume the return distributions for the market risks. The second one is to use the variances and co-variances across the market risks, and the third one is to run hypothetical portfolios through historical data or by using Monte Carlo simulations.

Simulation models are widely used in VaR applications since they help in understanding any potential risks in an investment decision, and in preparing for the possibility of a catastrophic outcome even though it might have a small probability of occurring. There are a number of recently proposed simulation methods for generating reliable VaR estimates due to the flexibility they offer. Huang (2010) proposes a Monte Carlo Simulation VaR model that accommodates recent market conditions in a general manner. By applying the methodology on the S&P 500 returns he finds that the VaR estimation via the proposed optimization process is reliable and consistent, producing better back-testing outcomes for all out-of-sample periods tested. By simulating the value of an asset under a variety of scenarios not only the possibility of falling below the desirable level can be identified, but there can also be measures taken to prevent this event from occurring in the future.

With the Monte Carlo simulations method the VaR of an asset or a portfolio is quantified as the maximum loss in the random variables distribution, associated with the appropriate percentile. In order to calculate the VaR, first the dynamics of the underlying processes i.e. prices, volatilities etc. need to be specified. Second, N sample paths need to be generated by sampling changes in the value of the asset or individual assets that comprise a portfolio (risk factors), over the desired holding period. Third, all information enclosed in the probability distribution needs to be incorporated. Fourth, using the N sample paths the value of each underlying risk factor needs to be determined, given the assumed process for each one. Finally, the individual values need to be used to determine the value of the asset/portfolio at the end of the holding period.

Monte Carlo simulation as a method use for estimating VaR is based on the assumption that prices follow a certain stochastic process, and thus by simulating these processes one can yield the distribution of the asset's value for the predetermined period. By simulating jointly the behaviour of all relevant market variables to generate possible future values, the Monte Carlo simulations method allows for the incorporation of future events affecting the market as well as the additions of jumps or extreme events, thus accurately modelling the market's behaviour. In VaR applications, the required quantile for both the left and the right tails can be obtained directly from the random paths. Monte Carlo simulation is a powerful tool for energy risk management that owes its increased popularity to its flexibility. It can incorporate in the modelling procedure all the important characteristics of the energy markets' behaviour such as seasonality, fat tails, skewness and kurtosis, and is also able to capture both local and non-local price movements. It is mostly due to this flexibility that Duffie and Pan (1997), and So, Chen, Lee and Chang (2008) conclude that the Monte Carlo approach is probably the best VaR methodology. The only troubling issue with the Monte Carlo approach is the fact that it is relative complex to implement, and that it can be computationally demanding.

Research Methodology

The data for the study is the historical daily crude oil future price between April 4, 1983 and April 4, 2011 sourced from Energy Information Administration. Data on a hypothetical Okoro field discussed in detail below was also used in this study. The profitability analysis of the data was done using Monte Carlo based VaR technique to show the risk analysis and investment decision on the Okoro field project.

The **Okoro Oilfield** is located 12 kilometers offshore Nigeria in an average depth of 46 fts in the eastern Niger Delta. Okoro was discovered by Japan Petroleum in 1973 with the drilling of okoro-1 well. The well penetrated the two oil bearing sands of about 1,700 m in the Agbada Formation and was logged and tested.

Okoro-2 follow up appraisal well was drilled one year later at the eastern extension of the field but it was water wet. Okoro-2 appraisal well confirmed the presence of both reservoir sands. The field is covered by good quality 3D seismic data which was acquired by Mobil Corporation.

Appraisal: An appraisal well Okoro -3 was spudded in 2006 by the Seadrill 7 jack-up rig on the Okoro Field. The well was drilled 1.5 kilometres (0.93 mi) east of the Okoro-1 discovery well. Okoro-3 was drilled as a vertical well and reached total depth of 2,000 m in the Miocene Agbada Formation. The well confirmed the eastern extension of the field and also the hydrocarbon contacts seen in both sand formations in the initial discovery. A full suite of modern log and pressure data was acquired and the well was successfully tested.

Following completion of testing operations, a second appraisal well Okoro 3 ST was drilled in December 2006. The well was drilled as a deviated sidetrack from the Okoro-3 wellbore and was designed to further evaluate both reservoirs and provide greater control for planning future horizontal production wells. The Okoro-3 side track was drilled at a maximum inclination of 55 degrees to the west of Okoro-3 and reached a total depth of 2,090 m. A full suite of pressure and log data was acquired and, as planned, the well was not tested. A total of 21 m (True Vertical Depth) of net oil pay was encountered, which was greater than expected at this location.

This additional penetration of the Okoro field assisted in planning the horizontal wells required to develop the field. As a result of the two well appraisal drilling programme, the proved and probable reserves cases on the Okoro-Setu development was enhanced. NSAI reserves was upgraded to 240.8 million barrels (3.94×10^6 m^3) (gross 2P) from 150.5 million barrels (2.46×10^6 m^{3}for Okoro field and 300 million barrels (4.8×10^6 m^3) for combined Okoro and Setu fields. Reservoir modelling suggests a recovery factor >30% is achievable from 5 wells.

Development: In June 2006, Afren signed a Financing and Production Sharing and Technical Services Agreement with Amni for participation in the development of Okoro and Setu. Under the terms of the agreement, Afren will finance the development and appraisal programme. The investor will recover these costs with uplift on its capital, from over 90 per cent of the barrels produced, net of operating costs and royalties.

In January 2008, development drilling commenced from a subsea template using Transocean's Adriatic-6 jack-up rig. The 10-point fixed mooring system for the FPSO vessel was installed in January and the Armada Perkasa arrived in March 2008 and was hooked up to the anchor system. In May 2008, the wellhead platform was installed and flowline connections made.

Production: First Oil was achieved during June 2008 when production from the first two production wells drilled commenced at a rate in excess of 30,000 barrels per day (480 m^3/d) of oil of 27° API oil from each well. A further five wells were subsequently drilled, completed and brought onstream. The wells drilled were a mixture of horizontal and highly deviated penetrations of the reservoir intervals. Reservoir quality was typically at the higher end of expectations.

Production in 2009 averaged 86,000 barrels per day (3,000.4 m^3/d), ahead of pre development expectations for that period. This is as a result of better reservoir quality than incorporated into the original field simulation model, good aquifer support and water breakthrough from the existing production wells occurring much later than predicted. At least two infill targets have also been identified and will be drilled in 2010, adding reserves and incremental production volumes.

The following analysis was carried out to help Management decide whether to develop the Okoro and Setu field as a floating hub site equipped to receive, process and export production from other nearby prospects:

1. a. Ultimate facility capacity: 120,000barrels per day (bpd) and 260 million standard cubic feet per day(mmscf/d) (2 x 60,000 barrels per day processing trains).
   b. 2000+ feet of water
2. Hub prospects include the following:
   a. Okoro field – 60,000 bpd, 120 mmscf/d, 6 wells (Primary field development)
   b. Setu field – 30,000 bpd, 60 mmscf/d, 3 wells (Secondary field development)
3. A standardized subsea system would be utilized including the following:
   a. Interchangeable subsea trees
   b. Subsea manifold at each prospect location
   c. Insulated flowlines/manifold
4. Project execution drivers include the following:
   a. Form team by March following first appraisal well drill, Project work plan completed by June, Design basis completed by September of same year
   b. Drilling another appraisal well by June of same year- optional
   c. Beginning design, vessel identification and procurement of all long lead time items by April of same year
   d. Purchasing a vessel by September of same year
   e. Start development drilling by January of following year
   f. Predrill and complete as many wells as possible prior to FPF installation as "base case"
   g. Okoro production top priority

Table 1: Scenario 1, the Capital Expense (CAPEX) estimate breakdown

Okoro Area A	**$MM (P50 Basis)**
Drill (exluding appraisal well - keeper) (x 2 wells)	46.5 (drill total for 2 wells)
Complete (x 3 wells)	43.2 (complete total for 3 wells)
Subsea System	42
Flowlines [(1) 6"x8" infield and (1) 14" Export]	64
Umbilicals	3
Vessel (P90 $132 million)	104
Process Facilities	65
Engineering and Project Management (Vessel and Topside Facility)	20
Sub-total	387.7
Capitalized Staff (4%)	15.5
Rother Area A, Total	403.2
Okoro Area B	**$MM (P50 Basis)**
Drill (x 3 wells)	46.8
Complete (x 3 wells)	32.4
Subsea System	36
Flowlines (dual 6" pipe-in-pipe)	14
Umbilicals	3
Sub-total	132.2
Capitalized Staff (4%)	5.2

Run the simulation: This is the last step in the simulation.

Table 3:Summary of the model

Known input	
Discount rate	11%

Uncertain inputs		Distribution	Parameter1	Parameter2	Parameter3
Capital expenditures	#NAME?	Triangular	$403,200	$540,600	$687,200
Month 1 oil production (STB)	#NAME?	Log normal	60000	30000	
Annual decline rate in oil production	#NAME?	Log normal	3.6%	2.5%	
Month 1 price of oil ($/STB)	#NAME?	Triangular	$89.58	$89.58	$95.00
Annual trend in oil price	#NAME?	Normal	1%	1%	

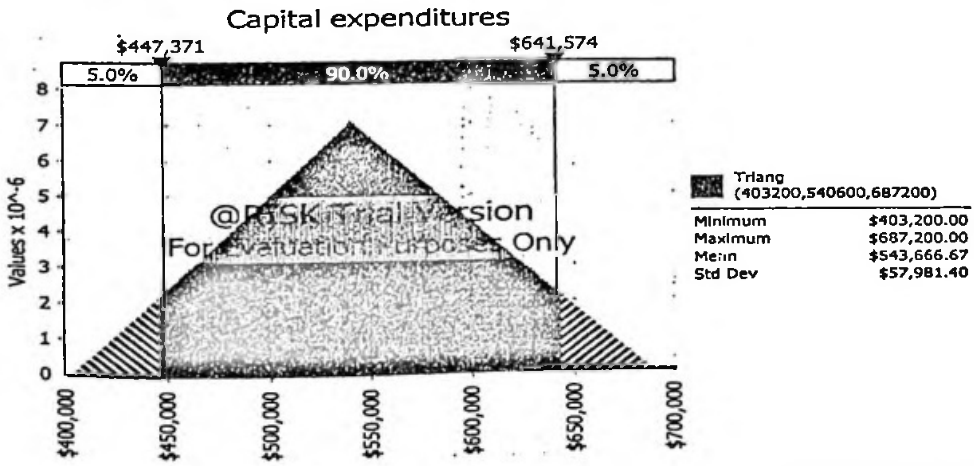
Economic model outputs								
End of month	1	2	3	4	5	6	...	24
Oil production (STB)	#NAME?	#NAME?	#NAME?	#NAME?	#NAME?	#NAME?	#NAME?	#NAME?
Price of oil	$78.40	$76.45	$81.29	$84.58	$74.12	$75.40	$76.38	$76.67
Oil revenue	#NAME?	#NAME?	#NAME?	#NAME?	#NAME?	#NAME?	#NAME?	#NAME?
Operating expenses	$438,333	$438,333	$438,333	$438,333	$438,333	$438,333	$438,333	$438,333
Net cash	#NAME?	#NAME?	#NAME?	#NAME?	#NAME?	#NAME?	#NAME?	#NAME?
NPV	#NAME?							

In the model, our known input is the Discount rate which is 11%, the historic crude oil future prices and the operating expenses.

The uncertain inputs and their distribution

Capital expenditure (CAPEX): One of the uncertain inputs is the capital expenditures – CAPEX – for Okoro A, Okoro B and Okoro & Setu oil field. The total capital expenditure for Okoro A was $403.2 million, Okoro B was $540.6 million and Okoro & Setu was $687.2 million. The distribution for the capital expenditure was triangular distribution. In a triangular distribution, the parameters are the minimum value, the most likely value, and the maximum value and the shape of the distribution is a triangle, with its peak at the most likely value.

Fig. 1: Distribution of the capital expenditure

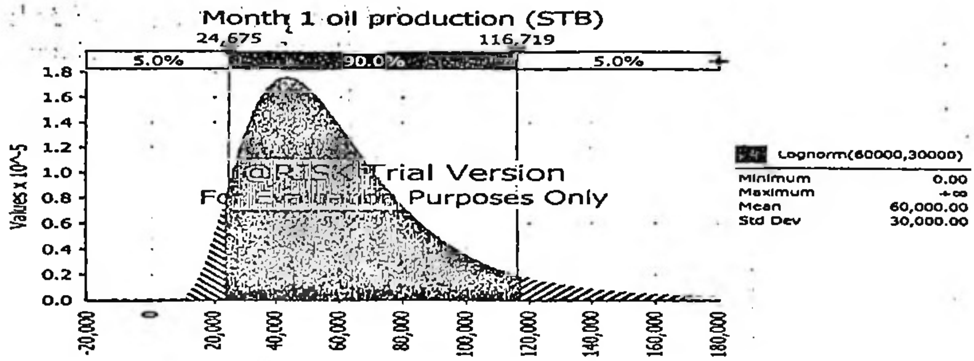


The triangular distribution is often used in business decision making, particularly in simulations because the most likely outcome is known, then the outcome can be simulated by a triangular distribution.

From the triangular distribution of the capital expenditure above, the maximum capital expenditure of $687.2 million lies above the upper 5% of the distribution while the minimum capital expenditure lies below the lower 5% of the distribution. The mean capital expenditure is $543.7 million while the standard deviation is $57.98 million.

Oil production: The oil production for Okoro A and B in the first month of production were 60000 STB and 30000 STB respectively. The lognormal distribution was used for the oil production because it is useful for modeling naturally occurring variables that are the product of a number of other naturally occurring variables. For instance, the volume of gas in a petroleum reserve is often normally distributed because it is the product of the area of the formation, its thickness, formation pressure, porosity and the gas:liquid ratio.

Fig.2: Distribution of oil production

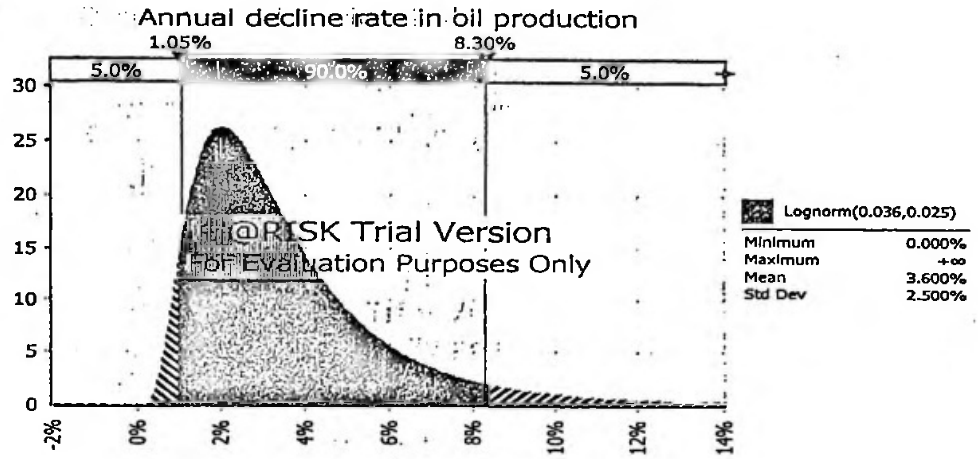


The lognormal distribution of the oil production shown above is skewed to the left showing that oil production is higher in the initial months than the preceding months as they will be decline in the production.

The minimum oil production is 0 STB i.e. when there is no production while the maximum oil production is infinity. The mean of the oil production was 60000 STB while the standard deviation was 30000 STB.

Decline rate in Oil production: The probability distribution for this is also the lognormal distribution as it is a naturally occurring factor. It is a product of supply and demand in the oil market. The distribution graph below shows that the average decline rate in oil price is 3.6% and the standard deviation of 2.5%.

Fig 3:Distribution of the decline in oil production

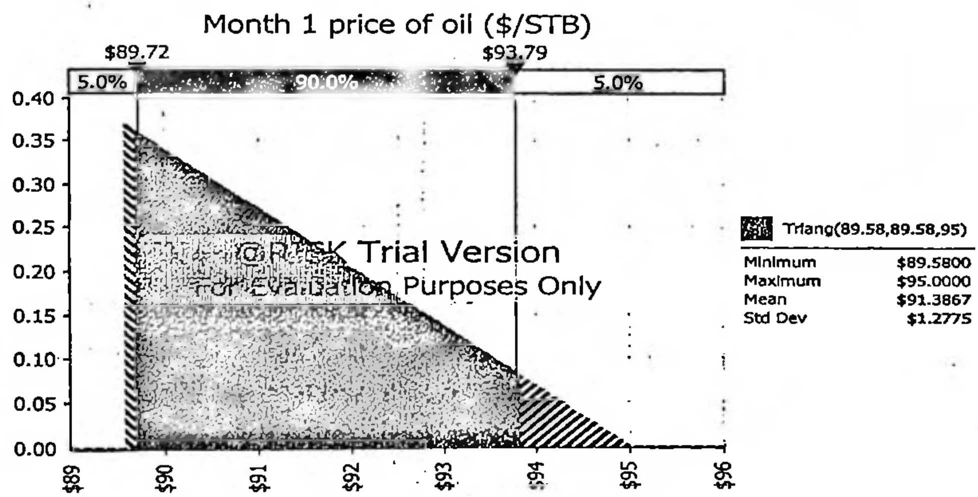


Month 1 price of oil per STB

The probability distribution for this was the triangular distribution. The triangular distribution was used because it shows the minimum value, the most likely value, and the maximum value and the shape of the distribution is a triangle, with its peak at the most likely value.

The graph of the distribution of the first month oil price is shown below in figure 4;

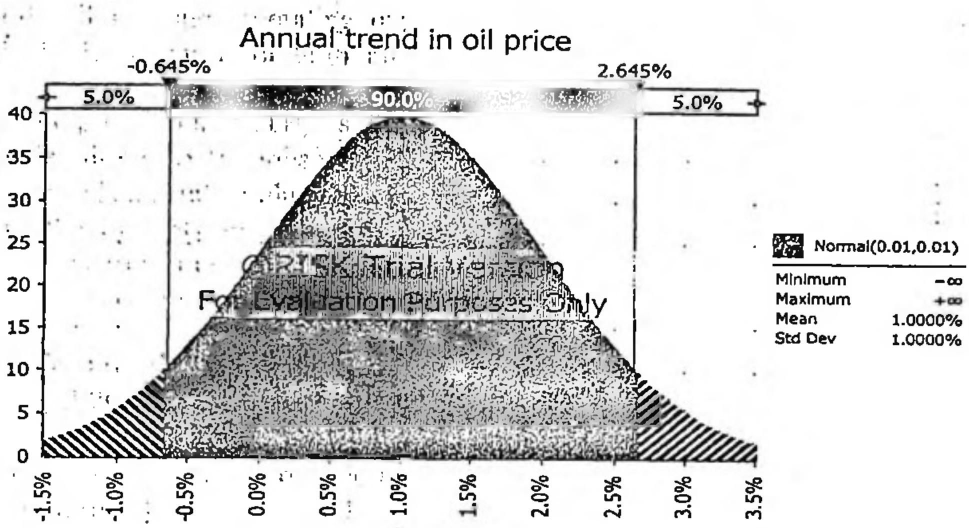
Fig. 4:Distribution of the price of oil



The graph shows the maximum price as $95 and the minimum price as $89. The mean and standard deviation of the oil price were $91.39 and $1.28 respectively.

Annual trend in oil price: The probability distribution used for the annual trend in oil price is the normal distribution. The normal distribution is used because It is observed that variations of a naturally occurring variable are approximately Normally distributed. The graph below shows the normal distribution of the annual trend in oil price.

Fig. 5: Distribution of annual trend in oil price



The graph shows that the mean and standard deviation of 1% and the maximum and minimum values are +∞ and -∞ respectively.

Economic Model Output: Under the outputs of the model, we have oil production (STB), price of oil, oil revenue, operating expenses, net cash and Net Present Value (NPV). All these variables have output for 24 months, the period of the observation.

The oil production (STB) is the monthly oil production output for the 24 months under consideration. The first observation is the production from the Okoro oil well for the first period and the subsequent production for the remaining 23 months was estimated based on the first using the monthly decline rate in our uncertain input. This oil production output will be decreasing from the first month based on the decline rate. This is because the oil reserve in any well cannot be increasing with production rather it will deplete.

The prices of oil used in the model were extracted from the Historic crude oil future prices for 2010 and 2011. These crude oil future prices were daily prices but we look for the average of the price for a month since we are interested in monthly analysis. These averages were found using arithmetic mean, by adding the prices in a month and dividing it by the number of observation.

The monthly oil revenue for the period of study was found by multiplying the oil production by the price of the oil for each month. These revenues were higher in some months than the others because of the differences in oil prices. It is expressed as;

$$\textit{Oil revenue} = \textit{Oil production} \times \textit{Oil price}$$

The operating expenses (OPEX) for the period of the study were estimated from the information on Okoro oil field. The operating expenses were fixed per well per month.

The net cash for the project was estimated as the difference between the oil revenue and operating expenses. Mathematically, it is expressed as

The net cash is the difference between the oil revenue and operating expenses. It is positively correlated with oil revenue since the operating expenses is fixed. The net cash behave the same way oil revenue behaves. The net cash is the same as the present value of cash inflow and the project under study, we have positive cash flows for all the months with the highest net cash flow of $4,265,667 occurring in the first month where oil production and oil revenue were the highest and the lowest net cash flow of $1,996,612 occurring at the 22nd month.

The Net Present Value for the project is $28,275,750 which is positive. The Net Present Value shows the viability of the project and since it is positive, the management can invest in the exploration of the Okoro and Setu oil field.

The graph and the grid on the next page provide a detailed explanation of the Net Present Value (NPV) of the project. It shows the maximum NPV, the minimum NPV, the mean, median and mode as well as the skewness and kurtosis.

The maximum NPV resulting from the simulation was $162,091,687 while the minimum NPV was about $1,153,138. This shows that the exploration of the oil field has no negative NPV. Whatever the case, the company will earn a return of atleast the minimum NPV. The mean NPV was $28,914,354 while the median and mode NPV were $25,114,475 and $15,946,007 respectively with a standard deviation of $17,278,937.

The skewness which is used in distribution analysis as a sign of asymmetry and deviation from a normal distribution was 1.6153. If Skewness > 0 (Right skewed distribution) most values are concentrated on left of the mean, with extreme values to the right. As can be seen from the graph below, the distribution is right skewed as extreme values are on the right of the distribution.

The kurtosis is used in the distribution analysis to measure the peakedness of the distribution. If Kurtosis > 3, it is a Leptokurtic distribution, sharper than a normal distribution, with values concentrated around the mean and thicker tails. This means high probability for extreme values. If Kurtosis < 3, it is a Platykurtic distribution, flatter than a normal distribution with a wider peak. The probability for extreme values is less than for a normal distribution, and the values are wider spread around the mean, and if Kurtosis = 3, it is a Mesokurtic distribution - normal distribution for example. The kurtosis of our NPV is 7.5951 which is > 3 shows that our distribution is leptokurtic.

From the graph, the values of the NPV are concentrated around the mean. The probability of having an NPV lower than $8.71 million is 5% and there are 5% chances of having an NPV greater than $61.81 million. In the same vein, there are 90% chances of having an NPV of $53.1 million. With this development, it is advisable for the company to undertake the project as the chances of having a positive return on investment are high.

Table 4: Simulation outputs

		Distribution	Parameter1	Parameter2	Parameter3
Discount rate	0.11				
Uncertain inputs					
Capital expenditures	543666.7	Triangular	403200	540600	687200
Month 1 oil production (STB)	60000	Lognormal	60000	30000	
Annual decline rate in oil production	0.036	Lognormal	0.036	0.025	
Month 1 price of oil ($/STB)	91.38667	Triangular	89.58	89.58	95
Annual trend in oil price	0.01	Normal	-0.01	0.01	

Economic model outputs

End of month	1	2	3	4	5	6	7	8	9	10	11	12
Oil production (STB)	60000	57878.42	55831.8538	53857.6558	51953.2649	50116.2127	48344.12	46634.68	44985.7	43395.01	41860.58	40380.4
Price of oil	78.4	76.45	81.29	84.58	74.12	75.4	76.38	76.67	75.55	81.95	84.31	89.23
Oil revenue	4704000	4424805	4538571.39	4555280.53	3850775.99	3778762.44	3692524	3575481	3398669	3556221	3529265	3603143
Operating expenses	438333	438333	438333	438333	438333	438333	438333	438333	438333	438333	438333	438333
Net cash	4265667	3986472	4100238.39	4116947.53	3412442.99	3340429.44	3254191	3137148	2960336	3117888	3090932	3164810

End of month	13	14	15	16	17	18	19	20	21	22	23	24
Oil production (STB)	38952.56	37575.21	36246.56297	34964.8951	33728.54671	32535.9152	31385.45	30275.67	29205.14	28172.45	27176.28	26215.34
Price of oil	89.58	89.74	102.98	110.04	101.36	96.29	97.34	86.34	85.61	86.43	97.16	98.51
Oil revenue	3489371	3371999	3732671.055	3847537.06	3418725.495	3132883.27	3055060	2614002	2500252	2434945	2640447	2582473
Operating expenses	438333	438333	438333	438333	438333	438333	438333	438333	438333	438333	438333	438333
Net cash	3051038	2933666	3294338.055	3409204.06	2980392.495	2694550.27	2616727	2175669	2061919	1996612	2202114	2144140
NPV	28275750											

The net cash is the difference between the oil revenue and operating expenses. It is positively correlated with oil revenue since the operating expenses is fixed. The net cash behave the same way oil revenue behaves. The net cash is the same as the present value of cash inflow and the project under study, we have positive cash flows for all the months with the highest net cash flow of $4,265,667 occurring in the first month where oil production and oil revenue were the highest and the lowest net cash flow of $1,996,612 occurring at the 22nd month.

The Net Present Value for the project is $28,275,750 which is positive. The Net Present Value shows the viability of the project and since it is positive, the management can invest in the exploration of the Okoro and Setu oil field.

The graph and the grid on the next page provide a detailed explanation of the Net Present Value (NPV) of the project. It shows the maximum NPV, the minimum NPV, the mean, median and mode as well as the skewness and kurtosis.

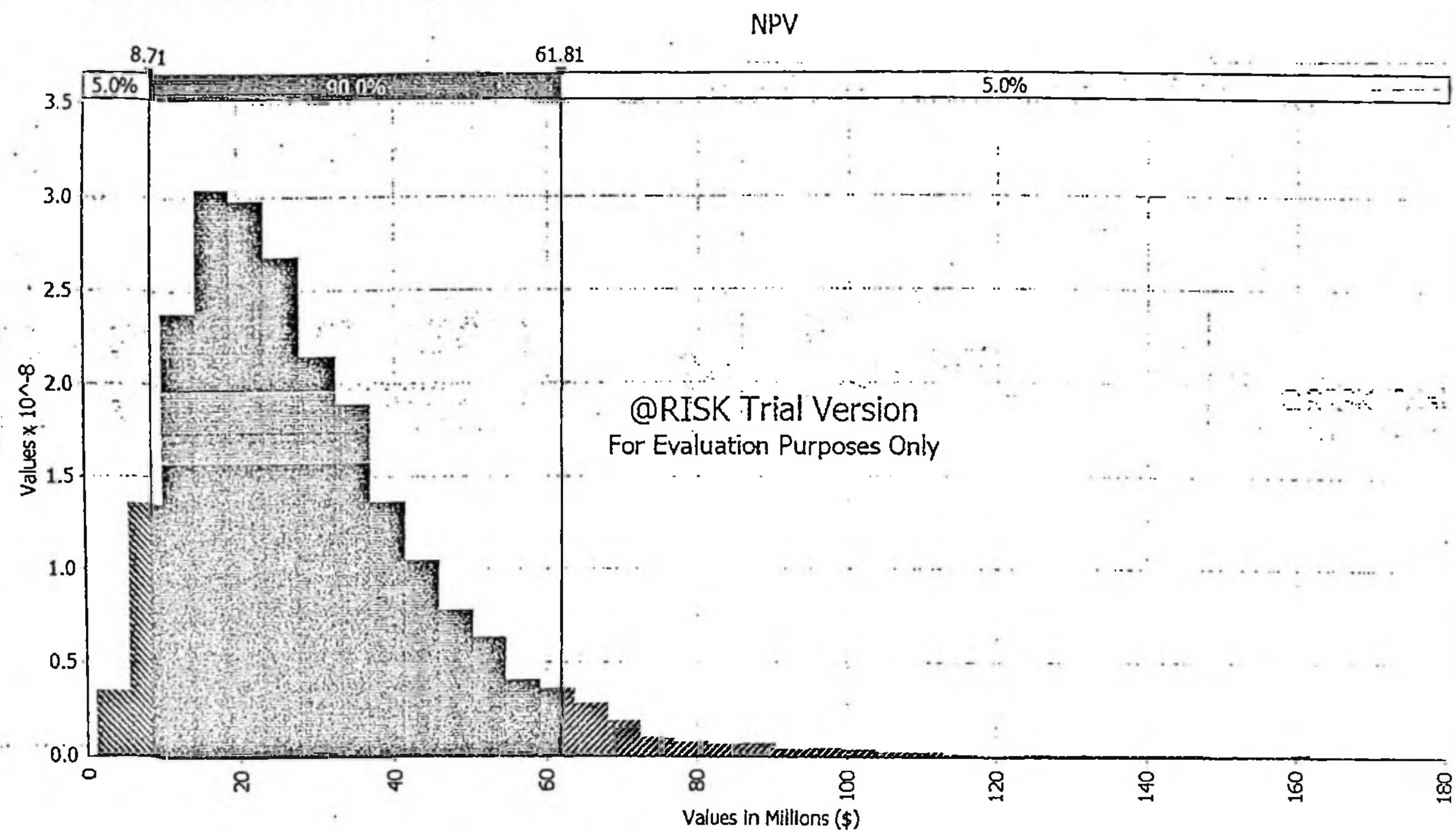
The maximum NPV resulting from the simulation was $162,091,687 while the minimum NPV was about $1,153,138. This shows that the exploration of the oil field has no negative NPV. Whatever the case, the company will earn a return of atleast the minimum NPV. The mean NPV was $28,914,354 while the median and mode NPV were $25,114,475 and $15,946,007 respectively with a standard deviation of $17,278,937.

The skewness which is used in distribution analysis as a sign of asymmetry and deviation from a normal distribution was 1.6153. If Skewness > 0 (Right skewed distribution) most values are concentrated on left of the mean, with extreme values to the right. As can be seen from the graph below, the distribution is right skewed as extreme values are on the right of the distribution.

The kurtosis is used in the distribution analysis to measure the peakedness of the distribution. If Kurtosis > 3, it is a Leptokurtic distribution, sharper than a normal distribution, with values concentrated around the mean and thicker tails. This means high probability for extreme values. If Kurtosis < 3, it is a Platykurtic distribution, flatter than a normal distribution with a wider peak. The probability for extreme values is less than for a normal distribution, and the values are wider spread around the mean, and if Kurtosis = 3, it is a Mesokurtic distribution - normal distribution for example. The kurtosis of our NPV is 7.5951 which is > 3 shows that our distribution is leptokurtic.

From the graph, the values of the NPV are concentrated around the mean. The probability of having an NPV lower than $8.71 million is 5% and there are 5% chances of having an NPV greater than $61.81 million. In the same vein, there are 90% chances of having an NPV of $53.1 million. With this development, it is advisable for the company to undertake the project as the chances of having a positive return on investment are high.

Fig. VI; Skewness of the output



Statistics	
Cell	Sheet1!B20
Minimum	$1,153,137.57
Maximum	$162,091,687.00
Mean	$28,914,354.34
Mode	$15,946,006.94
Median	$25,114,474.53
Std Dev	$17,278,936.86
Skewness	1.6153
Kurtosis	7.5951
Values	5000
Errors	0
Filtered	0
Left X	$8,707,771.39
Left P	5.0%
Right X	$61,809,247.41
Right P	95.0%
Dif. X	$53,101,476.02
Dif. P	90.0%
1%	$4,820,705.60
5%	$8,707,771.39
10%	$11,320,616.70
15%	$13,272,999.56
20%	$15,158,123.46
25%	$16,677,177.21
30%	$18,411,625.87
35%	$20,112,245.94
40%	$21,695,559.05
45%	$23,429,089.50
50%	$25,114,474.53
55%	$27,116,342.49
60%	$29,135,693.98
65%	$31,532,043.31
70%	$33,855,994.73
75%	$36,769,080.96
80%	$40,402,060.35
85%	$44,769,056.35
90%	$51,169,862.79
95%	$61,809,247.41

Conclusions

This paper studies the application of Monte Carlo VaR technique for risk analysis and investment decision in an oil exploration project. The data for the study was simulated 10000 times and the result shows the NPV of the project to be about $28.3 million which implies that the oil exploration project will be profitable since the NPV is positive.

The VaR in this study defined as the min NPV value that may result if the investment project is undertaken. This VaR is the maximum expected loss which the minimum NPV of $1.2 million represents. Based on the findings, the study concludes that Value-at-Risk, calculated by any method, is a reliable measure of oil price risk for whoever is concerned with oil price volatility, especially for firm manager or policy maker who are involve in decisions regarding capital investment like oil exploration.

This study recommends among others that the company should undertake the investment of oil exploration in the Okoro field area as chances of having a positive return on investment are high. Accurate calculation of VaR measures in the volatile energy markets is important for all market players as it allows managers to develop efficient hedging strategies to protect their investments. Lastly, with VaR model selection process, modeling risk can be minimized as it satisfies strict risk management requirements and control procedures, by reducing the probability of accepting flawed models.

References

Aloui, C. and Mabrouk, S. (2010):*Value-at-risk estimations of energy commodities via long-memory, asymmetry and fat-tailed GARCH models*, Energy Policy, 38, 2326-2339.

Bams, D., Lehnert, T., and Wolff, C.C.P. (2005):*An evaluation framework for alternative VaR models*. Journal of International Money and Finance, 24, 944-958.

Cabedo, J.D. and Moya, I. (2003):*Estimating oil price Value at Risk using the historical simulation approach*. Energy Economics, 25, 239-253.

Chiu, Y.C, Chuang, I.Y., and Lai, J.Y. (2010):*The performance of composite forecast models of value-at-risk in the energy market*. Energy Economics, 32, 423-431.

Duffie, D. and Pan, J. (1997):*An overview of value at risk*. Journal of Derivatives, 4, 7-49.

Giot, P. and Laurent, S. (2003):*Market risk in commodity markets: A VaR approach*. Energy Economics, 25, 435-457.

Hibon, M. and Evgeniou, T. (2005):*To combine or not to combine: selecting among forecasts and their combinations*. International Journal of Forecasting, 21, 15-24.

Huang, A.Y. (2010):*An optimization process in Value-at-Risk estimation*. Review of Financial Economics, 19 (3), 109-116.

Huang, J.C., Lee, M.C., and Liu, H.C. (2008):*Estimation of value-at-risk for energy commodities via fat-tailed GARCH models*. Energy Economics, 30, 1173-1191.

Krehbiel, T. and Adkins, L.C. (2005):*Price risk in the NYMEX energy complex: An extreme value approach*. Journal of Futures Markets, 25 (4), 309-337.

Marimoutou, V., Raggad, B., and Trabelsi, A. (2009):*Extreme Value Theory and Value at Risk: Application to oil market*. Energy Economics, 31 (4), 519-530.

Mehdi, S. and Saeed, S. (2006):*Energy risk management and value at risk modelling*. Energy Policy, 34 (2006) 3367–3373.

Mittnik, S. and Paolella, M.S. (2000):*Conditional density and value at risk prediction of Asian currency exchange rates*. Journal of Forecasting, 19, 313-333.

Nomikos, N., Pouliasis, P. (2011):*Forecasting petroleum futures markets volatility: The role of regimes and market conditions*. Energy Economics, 33 (2), 321-337.

Sadeghi, M. and Shavvalpour, S. (2006):*Energy risk management and value at risk modeling*. Energy Policy, 34, 3365-3373.

So, M., Chen, C., Lee, J., and Chang, Y. (2008):*An empirical evaluation of fat-tailed distributions in modelling financial time series*. Mathematics and Computers in Simulation, 77, 96-108.