

Probabilistic Approach of Petroleum Reserves Estimation

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Abstract—*The study evaluates probabilistic modeling for accurate estimation and classification of petroleum reserves for strategic decision-making, financial planning, and regulatory compliance in the oil and gas sector. Traditional deterministic methods, which use single-point estimates for reservoir and economic parameters, often fail to reflect the full range of uncertainty in subsurface and market conditions. In this study, a probabilistic approach was applied using Monte Carlo simulation with 10,000 iterations to model uncertainties in key reservoir parameters such as porosity with range of (12–22%), water saturation (25–40%), net thickness (15–30 m), formation volume factor (1.05–1.35), and recovery factor (25–38%)—as well as economic variables including oil price (\$55–\$85/bbl), operational expenditure (OPEX), capital expenditure (CAPEX), and discount rate (8–14%). The simulation produced recoverable reserves estimates of P90 = 4.5 MMbbl, P50 = 11.92 MMbbl, and P10 = 21.39 MMbbl, compared to a deterministic estimate of 12 MMbbl. Corresponding Net Present Values (NPVs) at a 10% discount rate were P90 = \$14.80 million, P50 = \$17.29 million, and P10 = \$21.51 million, with an Expected Monetary Value (EMV) P90 = \$12.58 million, P50 = \$14.69 million, and P10 = \$17.05 million. Sensitivity analysis revealed oil price and discount rate as the most influential drivers of economic outcomes, followed by recovery factors. Compared to deterministic estimates, the probabilistic method reduced uncertainty by quantifying confidence levels. The results demonstrate that probabilistic techniques provide novel approach to risk-adjusted investment decisions.*

Key Words—*Expected Monetary Value, Net Present Value, Discount rate, Operating Expenditure, Sensitivity*

I. INTRODUCTION

Conventional deterministic reserve estimation, which commonly uses single “low,” “best,” or “high” values for uncertain parameters, does not fully represent the range of possible reserve outcomes. Probabilistic reserve estimation provides an alternative framework by assigning probability distributions to uncertain parameters and propagating these uncertainties through a reserve estimation approach (Lee, 2008; Demirmen, 2007; Worthington, 2007). The importance of explicitly characterizing uncertainty

has also been emphasized within the Petroleum Resources Management System (PRMS), where probabilistic methods and scenario-based approaches are recognized for evaluating petroleum resources and reserves.

The probabilistic approach involves treating reservoir and production variables such as gross rock volume, net-to-gross ratio, porosity, water saturation, formation volume factor, recovery factor, and production decline parameters as uncertain quantities rather than fixed values. Probability distributions are assigned to these parameters based on geological interpretation, well data, seismic information, analogues, engineering analysis, or expert judgment. Monte Carlo simulation can then repeatedly sample from these distributions to generate a distribution of possible reserve outcomes (Divi, 2004). This enables engineers and geoscientists to quantify uncertainty and report reserve estimates at different probability levels, commonly expressed using measures such as P90, P50, and P10.

Several studies have demonstrated the practical application of probabilistic methods to petroleum reserves estimation. Cheng et al., (2010) applied a probabilistic approach to decline curve analysis and demonstrated its usefulness for quantifying uncertainty in reserves derived from production data. Similarly, Jochen & Holditch (1996) examined probabilistic reserve estimation using decline-curve analysis and the bootstrap method, providing an approach for generating reserve distributions without requiring predetermined parameter distributions. Snow et al., (1996) also demonstrated how Monte Carlo-type parameter sampling could integrate reserve uncertainty with exploration risk and economic evaluation.

Eriçok & Gümrah (2010) used probability distributions for uncertain reservoir variables and Monte Carlo simulation to evaluate probable reserves in a naturally fractured carbonate reservoir. Karacaer & Onur (2012) investigated analytical probabilistic

reserve estimation using the volumetric method and addressed the aggregation of resources. Khisamov et al., (2018) examined probabilistic-statistical reserve estimation within the SPE-PRMS framework and discussed the application of Monte Carlo techniques to petroleum reserves and resources.

Mohammed et al.,(2018) applied Monte Carlo simulation to quantify uncertainty in multi-layered reserve estimation and emphasized that uncertainties in petrophysical parameters and data acquisition can influence reserve forecasts. Adeigbe, Odedere, and Amodu (2018) applied Monte Carlo simulation to quantify uncertainty in ultimate recoverable reserves for the OWA marginal field, demonstrating the usefulness of stochastic estimation for Nigerian petroleum assets. More recent work has combined probabilistic simulation with advanced reservoir modelling and physics-informed approaches to improve uncertainty quantification in Niger Delta reserve estimation (Ngu et al., 2026).

Rather than producing only a single reserve number, the probabilistic estimation provides a range of possible outcomes and their associated probabilities. Harrison & Falcone (2017) argued that probabilistic language can provide a clearer way of communicating uncertainty associated with petroleum project. Galvao et al, (2012) further addressed probabilistic reserves and resources estimation and the aggregation of probabilistic estimates.

Other researchers have examined the combination of deterministic and probabilistic approaches. Quirk et al., (2017) discussed combined deterministic-probabilistic methods for estimating undiscovered hydrocarbon resources. Wallace (1993) also examined the relationship between probabilistic reserve distributions and reserve categories, highlighting important considerations concerning the use of probability percentiles to represent confidence levels.

Therefore, the probabilistic approach to petroleum reserves estimation provides a systematic means of incorporating uncertainty into reserve calculations and presenting results as probability distributions rather than single deterministic values. The increasing application of Monte Carlo simulation, Bayesian methods, uncertainty quantification, and integrated reservoir modelling demonstrates the

continuing importance of probabilistic techniques in modern petroleum-reserves assessment.

II. METHODOLOGY

Petrophysical and reservoir data such as porosity, net pay, water saturation, formation volume factor, and recovery factor were sourced from literature (SPE repository). Economic parameters, such as oil price, operational expenditure (OPEX), capital expenditure (CAPEX), and discount rates were obtained from industry reports and existing literature. All input parameters were defined using probability distributions based on statistical analysis of their variability. @RISK (Palisade Decision Tools Suite) was used for Monte Carlo simulation and Microsoft Excel used for data handling and preliminary calculations

2.1 Modeling Uncertainty in Reservoir Parameters

Reservoir parameters such as net reservoir thickness (h), porosity (ϕ), water saturation (S_w), formation volume factor (B_o), and recovery factor (RF) were treated as random variables to reflect the inherent uncertainty and variability found in subsurface data. Probability distributions were assigned that best represent the range and frequency of their possible values based on available geological, petrophysical, and reservoir engineering data.

The selection of probability distributions for each parameter was informed by historical field data, expert judgment, and literature benchmarks and presented as follows;

- i. Porosity followed a normal distribution if data indicates a symmetrical spread around a mean value.
- ii. Water saturation followed a beta distribution, suitable for bounded variables between 0 and 1.
- iii. Net thickness and formation volume factor was modeled using triangular or log-normal distributions, especially where data are skewed or limited.

Once distributions were assigned, a Monte Carlo simulation was performed @RISK. 10,000 iterations of the volumetric reserves' estimation were run during the simulation. The reserves estimation is shown in equation (1).

$$\text{Reserves (STB)} = 7758 \times A \times h \times \phi(1 - S_w) \times \frac{1}{B_o} \times \text{Recovery Factor} \quad (1)$$

Where, A = area of the reservoir (acres), h = net pay thickness (feet), ϕ = porosity (fraction), S_w = water saturation (fraction), B_o = formation volume factor (RB/STB), RF = recovery factor (fraction), 7758 is

the conversion factor from acre-feet to stock tank barrels (STB). Table 1 and 2 presents the input parameters of the reserve estimation and economic parameters for economic evaluation respectively.

Table 1: Inputs Parameters for Reserves Estimation

Parameter	Symbol	Unit	Distribution Type	Min / Low	Most Likely (Mean)	Max / High
Area	A	acres	triangular	1100	1200	1300
Net Pay Thickness	H	feet	Triangular	30	50	70
Porosity	Φ	fraction	Normal	-	0.21 (mean)	-
Water Saturation	S_w	Fraction	Beta	0.20	-	0.45
Formation Volume Factor B_o		RB/STB	Lognormal	1.05	1.2	1.35
Recovery Factor	RF	Fraction	Triangular	0.15	0.25	0.35

Table 2: Economic Parameters

Parameter	Symbol	Unit	Distribution Type	Min / Low	Most Likely (Mean)	Max / High
Oil Price	-	\$/bbl	Triangular	55	70	90
OPEX	-	\$/bbl	Normal	-	12	-
CAPEX	-	\$ million	Triangular	20	30	40
Discount Rate R	%		Triangular	8	10	12

Each iteration randomly samples values from the defined input distributions and computes a corresponding reserve volume. The result is a probabilistic reserves distribution, typically presented in terms of:

- P90 (Proved Reserves, 1P) – 90% probability that the reserves will equal or exceed this value.
- P50 (Probable Reserves, 2P) – 50% probability of exceedance.
- P10 (Possible Reserves, 3P) – 10% probability of exceedance.

The outcome of the simulation is a reserve probability density function (PDF) and cumulative distribution function (CDF) that provide a complete picture of the range and likelihood of different reserve outcomes. This approach enables more robust classification and risk-based decision-making, as opposed to relying on single-point deterministic estimates

2.2 Classification into 1P, 2P, and 3P Categories

The simulation output, generated from the Monte Carlo analysis, yields a large distribution of reserve values based on thousands of combinations of input parameters. This output provides a comprehensive view of the range and likelihood of different reserve volumes, from the most conservative to the most optimistic scenarios.

To enable standardized classification and facilitate decision-making, the results are interpreted using three key probabilistic percentiles:

- P90 (1P – Proved Reserves): This is the reserve volume that has a 90% probability of being equaled or exceeded. It reflects a high level of confidence and low risk.
- P50 (2P – Proved + Probable Reserves): This is the reserve volume with a 50% probability of being exceeded.
- P10 (3P – Proved + Probable + Possible Reserves): This reserve volume has only a 10% chance of being exceeded. It captures the upper limit of expected reserves and is used in assessing

upside potential or best-case scenarios. However, it is associated with higher risk and uncertainty.

2.3 Economic Evaluation Using Probabilistic Reserves Classification

Following the classification of petroleum reserves into 1P (proved), 2P (proved + probable), and 3P (proved + probable + possible) categories using Monte Carlo simulation, the study proceeds to evaluate the economic implications of these reserve estimates. This evaluation was performed using a model that incorporates the probabilistic reserves data to compute key financial metrics critical for petroleum investment decision-making. These include:

i. Net Present Value (NPV)

The NPV was computed with equation (2):

$$NPV = \sum_{t=1}^n \frac{R_t - C_t}{(1+r)^t} \quad (2)$$

Where: R_t = revenue in year t , C_t = capital and operating costs in year t , r = discount rate, n = project life in years

ii. Expected Monetary Value (EMV)

The Expected Monetary Value (EMV) integrates both the probability and the financial impact of various reserve scenarios, offering a risk-weighted economic forecast. It is computed as:

$$EMV = (P_{90} \times NPV_{90}) + (P_{50} \times NPV_{50}) + (P_{10} \times NPV_{10}) \quad (3)$$

This approach ensures that decisions are based not only on potential returns but also on the likelihood of achieving those returns.

$$EMV = \sum_{i=1}^n P_i \times NPV_i \quad (4)$$

$$\sum_{i=1}^n P_i = 1 \quad (5)$$

If we deliberately define Low case/1P, Base case/2P, High case/3P with probabilities:

$$P_1 + P_2 + P_3 = 1 \quad (6)$$

then:

$$EMV = P_1 p(NPV_{1p}) + P_2 p(NPV_{2p}) + P_3 p(NPV_{3p}) \quad (7)$$

2.4 Sensitivity Analysis

A sensitivity analysis was conducted to examine how variations in key economic and technical parameters affect project viability. The following parameters were tested :

- i. Oil price – a volatile market factor with significant impact on revenue and NPV.
- ii. Operating expenditure (OPEX) – directly influences net cash flow and IRR.

- iii. Recovery factor (RF) – a reservoir parameter that affects recoverable reserves volume.

Each of these variables was adjusted across a realistic range while holding other inputs constant, and the resulting changes in NPV and IRR recorded. This identifies the most sensitive variables and informs strategies for managing economic risk.

2.5 Comparative Assessment with Deterministic Economic Forecasts

To highlight the practical value of the probabilistic approach, the economic outcomes derived from probabilistic reserve scenarios were compared to those obtained using a deterministic method. In deterministic analysis, single-point (mean or most-likely) values are used for each input parameter, producing a single NPV or IRR estimate.

Key comparisons include:

- i. Differences in NPV and IRR across deterministic and probabilistic scenarios.
- ii. The extent to which deterministic models may underestimate or overestimate project value.
- iii. The risk exposure ignored in deterministic models versus that captured in probabilistic models.
- iv. The implications for investment decision-making, financing, and project risk management.

2.6 Economic Assumptions

- i. Oil price was not treated as a perfectly constant parameter throughout the analysis. Instead, appropriate scenarios or probability ranges were considered to reflect possible price variability over the project life.
- ii. Capital expenditure was allowed to vary within defined uncertainty ranges to account for possible cost escalation and project execution uncertainty.
- iii. Operating expenditure was assigned an uncertainty range where applicable.
- iv. Discount rate sensitivity was evaluated because changes in the cost of capital can significantly influence the estimated NPV.

2.7 Modelling of Oil Price Uncertainty

For the Monte Carlo simulation, the oil price was represented using an appropriate probability distribution. During each simulation iteration, a

different oil price value was sampled from the specified distribution, and the resulting cash flow and NPV were calculated. The approach enabled the economic model to capture the potential effects of market volatility on project profitability and provided a more realistic representation of the uncertainty associated with future petroleum revenues.

2.8 Basis Risk Consideration

The study recognizes that the benchmark oil price used in the economic model may differ from the actual realized price received for the crude oil produced from the field. This difference may arise from crude quality differentials, transportation costs, market location, contractual arrangements, and regional pricing conditions.

To account for this uncertainty, the oil price realized may be expressed as presented in equation(8)

$$P_{realized} = P_{benchmark} + D \quad (8)$$

Where:

- $P_{realised}$ = Actual oil price
- $P_{benchmark}$ = Assumed benchmark oil price
- D = Price differential or basis adjustment

The price differential may also be varied probabilistically or examined through sensitivity scenarios. This allows the economic model to account for the possibility that actual field revenues may differ from those predicted using the benchmark oil price alone.

2.9 Selection of Probability Distributions for Uncertain Reservoir Parameters

In the probabilistic reserve estimation model, the principal reservoir parameters were treated as uncertain variables rather than fixed deterministic quantities. Appropriate probability distributions were assigned to each parameter based on the nature of the available data, the expected physical range of the parameter, and the degree of available geological and reservoir information.

The selection of probability distributions was intended to represent the realistic variability of the input parameters during the Monte Carlo simulation. Parameters with limited data but known minimum, most likely, and maximum values were represented using triangular distributions, while parameters supported by sufficient statistical data could be represented using normal, lognormal, beta, or other appropriate distributions.

2.10 Economic Evaluation Depth

Net present value was evaluated using Using the correlation present in equation (9)

$$NPV = \sum_{t=1}^n \frac{R_t - C_t}{(1 + r)^t} - I_0 \quad (9)$$

Where:

NPV= Net Present Value, R_t = Revenue in year
, C_t = Total cost in year , r = Discount rate t =
Project life , I_0 = Initial capital investment.

2.11 Development of the Production Profile

The annual production profile used in the economic model was derived from the estimated recoverable reserves and the assumed field development and depletion strategy. The production profile was constructed to ensure that cumulative production over the project life did not exceed the recoverable reserve associated with each reserve scenario.

For each reserve case, the production forecast was developed using an appropriate production profile based on the available field information. Where detailed historical production data were unavailable, a simplified production forecast was developed using an assumed plateau period followed by a decline phase.

The cumulative production was constrained by:

$$N_p \leq N_R$$

Where N_p = cumulative oil production recoverable, N_R =Recoverable reserves

Production model can be presented as follows in equation (10)

$$q_t = q_i e^{-Det} \quad (10)$$

q_t = production rate at time t , q_i =initial production rate, De =effective decline rate , t = production time.

The production profiles for the 1P, 2P, and 3P reserve cases were subsequently used to generate annual production volumes and revenue streams for the NPV and IRR calculations.

2.12 Royalty and tax

The initial economic analysis was conducted on a simplified pre-tax basis and did not explicitly incorporate detailed royalties and taxation. This was identified as a limitation because fiscal obligations can materially affect petroleum project profitability.

2.13 Project Life Assumption

The project life was defined based on the production profile and the economic limit of field operation.

Production was assumed to continue until the recoverable reserve had been substantially depleted or until the production rate declined to the specified economic limit. The project life was therefore determined using Estimated recoverable reserves, Production plateau duration, Production decline rate, Minimum economic production rate. And Field development and abandonment schedule. The assumed project life was 20 years. This period included the development, production, and abandonment phases where applicable.

2.14 Discount Rate Range

The discount rate range of 8-12% was selected to represent uncertainty in the cost of capital and the risk associated with petroleum project investment. The lower value represents a relatively favourable financing and lower-risk condition, while the upper value represents increased financing cost and project risk. The base case discount rate was selected based on the assumed weighted average cost of capital or the minimum required return for the project, while the lower and upper values were used for sensitivity analysis rather than as arbitrary assumptions.

2.15 Sensitivity Analysis

The variables evaluated included, Oil price, CAPEX, OPEX, Recovery factor, Reservoir area, Net pay thickness, Porosity, Water saturation, Discount rate and Production rate

The percentage variation applied to each parameter was based on the uncertainty range adopted in the study.

The sensitivity of NPV to each parameter was evaluated using:

$$\% \Delta NPV = \frac{NPV_{new} - NPV_{base}}{NPV_{base}} \times 100$$

(11)

The results were presented using tornado diagrams to rank the relative influence of the input variables and spider plots to illustrate the relationship between changes in individual parameters and the resulting NPV.

2.18 Economic Assumptions for the Deterministic Case

The deterministic economic evaluation was conducted using clearly defined base-case assumptions for oil price, CAPEX, OPEX, production profile, discount rate, and applicable fiscal terms. The deterministic assumptions are presented in Table 3

Table 3: Deterministic Assumptions

Parameter	Symbol	Unit	Deterministic assumptions
Area	A	acres	1200
Net Pay Thickness	H	Feet	50
Porosity	Φ	fraction	0.21 (mean)
Water Saturation	Sw	Fraction	-
Formation Volume Factor	Bo	RB/STB	1.2
Recovery Factor	RF	Fraction	0.25
Oil Price	-	\$/bbl	70
OPEX	-	\$/bbl	12
CAPEX	-	\$ million	30
Discount Rate	R	%	10

III. RESULTS

3.1 Model Uncertainties for Reserves Estimation

Figure 1 presents the Monte Carlo simulation output for recoverable reserves, derived using @RISK software. The simulation incorporates uncertainty in key reservoir parameters net pay thickness, porosity (ϕ), water saturation (Sw), formation volume factor (Bo), and recovery factor (RF) and calculates reserves using the probabilistic volumetric method.

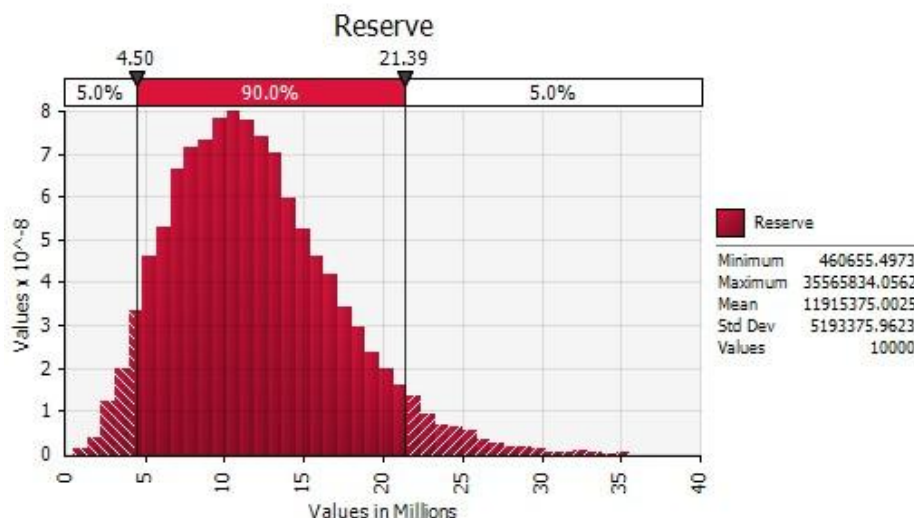


Figure 1: Reserve Estimation based on Probabilistic Data

The output distribution is positively skewed (right-skewed), which is typical in reserve estimation due to the nature of subsurface uncertainty. The downside risk tends to be bounded (since parameters like net pay or porosity cannot go below zero), whereas upside potential is less constrained, leading to skewed distributions and agree with Rose (2001)

The results showed that the bulk of the reserve outcomes (90%) lie between approximately 4.5 and 21.4 million barrels, aligning with P90-P10 range, providing a 90% confidence interval. The mean reserve estimate was around 11.9 million barrels, which corresponds to the P50 or "most likely" value, useful for development planning and financial modeling. The maximum reserve exceeds 35 million barrels, indicating that while high reserve volumes are possible, their probability of occurrence is low with critical insight for risk-aware investment planning.

The statistical minimum of 0.461 million stock tank barrels (MMSTB) represents the extreme lower bound of the simulated outcomes. This corresponds to an extremely pessimistic scenario where most reservoir and economic conditions are unfavorable. The maximum value of 35.57 MMSTB represents the optimistic tail of the distribution. This reflects a scenario where reservoir parameters simultaneously align at or near their most favorable values. The mean reserve estimate which lies close to the P50 percentile serves as a central tendency of the simulation. This value represents the expected or most likely estimate and is commonly used for planning purposes such as

budgeting, field development strategy, and investment screening.

3.2 Probabilistic Reserve Values

Table 4 summarizes the Monte Carlo simulation output for probabilistic reserve percentiles P90 (1P), P50 (2P), and P10 (3P) which reflect the inherent uncertainty in petroleum reserve estimation. The P90 value of 4.50 MMSTB indicates a 90% probability which indicates that the actual recoverable reserves will equal or exceed this value. This represents the proved reserves, a conservative estimate commonly used for Regulatory reporting, Financing decisions and Field development approval.

Table 4: Probabilistic Reserve Categories

Reserve Class	Value (MMSTB)
P90 (1P)	4.50
P50 (2P)	~11.92 ($\approx$ mean)
P10 (3P)	35.57

P50 value of 11.92 MMSTB implies a 50% chance that reserves will exceed this volume, representing a balanced or "best estimate". The P10 value of 35.57 MMSTB reflects a 10% probability of exceedance, representing possible reserves. P90 (4.50 MMSTB) is appropriate for development planning and securing financing, as it aligns with capital risk-aversion. P50 (11.92 MMSTB) Serves as the base case for internal project valuation and NPV modeling. P10 (35.57 MMSTB) is used for communicating upside to investors or partners and guiding exploration/appraisal strategies.

3.3 Classification of Petroleum Reserves into Proved (1P), Probable (2P), and Possible (3P) Categories using Probabilistic Output.

Figure 2 shows a Net Cash Flow distribution generated from a Monte Carlo simulation using

@RISK, showing the range of possible economic outcomes for a petroleum project based on uncertainty in key input parameters.

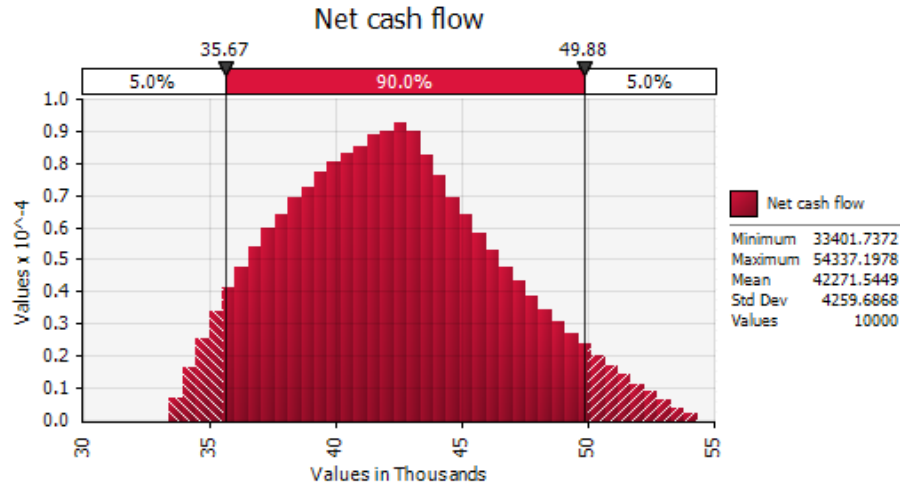


Figure 2: Net Cash Flow Probabilistic Modelling

The mean cash flow, approximately equal to the P50 percentile, represents the expected value across all simulations. It serves as a central estimate for financial modeling, development planning, and budgeting. In line with PRMS guidelines, the P50 (or mean) case balances conservatism with optimism, making it the preferred basis for internal economic evaluation. The standard deviation indicates moderate variability in projected cash flows. This spread reflects the inherent economic uncertainty, and signals that while outcomes vary, the risk is not extreme. The P90 (5th percentile), indicates that 90% of outcomes exceed this threshold thus, it is used for low-risk, conservative planning.

The results show the value of probabilistic economic modeling in petroleum projects. The broad yet well-distributed outcome range, captured through many simulations, provides a reliable basis for evaluating risk and return. Unlike deterministic models, this method embraces the complexity and variability inherent in reservoir and market conditions, leading to more resilient investment strategies. Figure 2 is slightly right-skewed, with the bulk of values falling between 38,000 and 46,000 USD in which most likely values lie around the

3.4 Net Present Value of Proved Reserve(1P)

Figure 3 shows the Net Present Value (NPV) simulation result, based on 10,000 Monte Carlo iterations, of the proved classification.

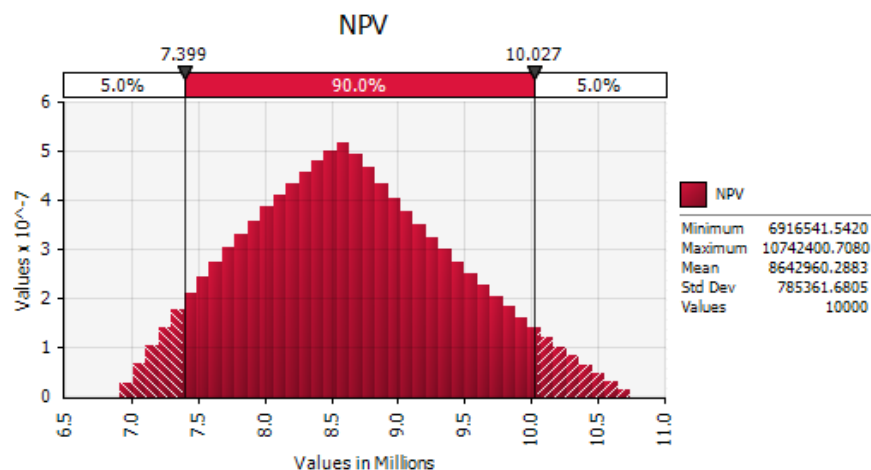


Figure 3: NPV Simulation Result in Terms of 1P (Proved)

The minimum value 6.92 million indicates the Worst-case economic outcome, the maximum value 10.74 million shows best-case scenario under favorable assumptions. The mean (P50) value of 8.65 million indicates the most likely expected NPV (base case). The standard deviation 785,362 shows moderate variability which reflects uncertainty due to input

variations, The P90 (5th percentile) of 7.40 million shows 1P – conservative estimate which is 90% chance that the project NPV exceeds this value. The P10 (95th percentile) which is 10.03 million indicates 10% chance of exceeding this value (high-risk, high-reward case). The P90 NPV value of \$7.399 million represents a high-confidence, low-risk estimate.

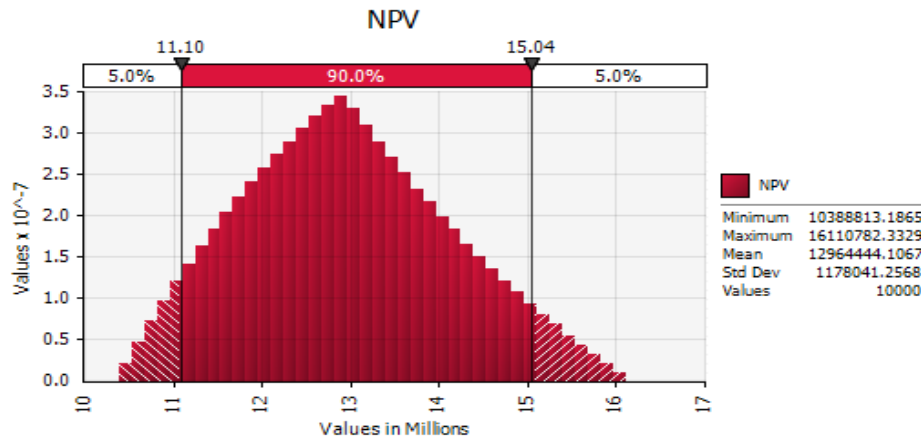


Figure 4: NPV of 2P (Proved + Probable Reserves)

The minimum value of \$10.39 million shows the worst-case scenario under pessimistic assumptions. The maximum value of \$16.11 million indicates best-case scenario under favorable inputs. The Mean ($\approx$ P50) value of \$12.96 million is the Most likely value which corresponds to 2P, the standard deviation of \$1.17 million which shows Moderate spread indicating manageable risk. The P90 (1P) of \$11.10 million shows 90% chance that actual NPV and exceeds this which is conservative. The P10 (3P) of \$15.04 million shows 10% chance NPV and exceeds the optimistic or upside case. The P50 (50th percentile) value of \$12.96 million is typically used to represent 2P reserves, which includes proved +

probable reserves. Figure 4 is nearly symmetrical, suggesting a well-behaved model, balanced risk between downside and upside and predictable outcomes, with the 90% confidence interval between \$11.10M and \$15.04M This symmetrical bell curve indicates no major skew, reflecting a mature and stable project with reduced uncertainty. The strategic applications of 2P (P50 = \$12.96M) is suitable for Planning & Budgeting, Use this base case for setting capital budgets and estimating expected returns.

3.5 Net Present Value of 3P

Figure 5 shows the net present value of 3p and table 4.6 indicates the estimated statistical values.

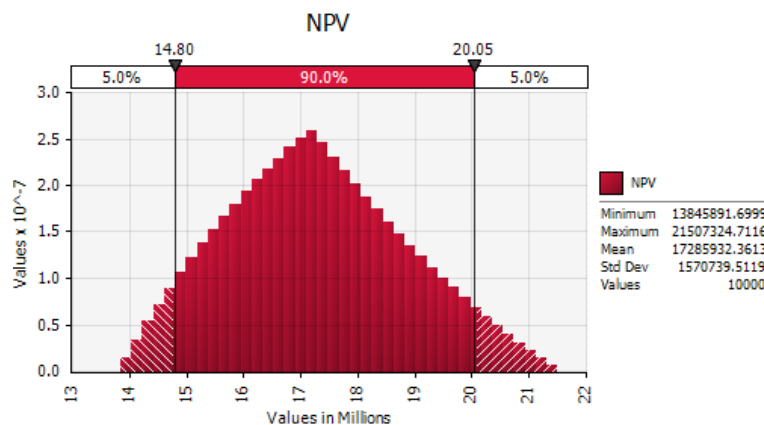


Figure 5: NPV of 3P (Proved + Probable + Possible Reserves)

The minimum value of \$13.85 million shows worst-case economic outcome. The maximum value of \$21.51 million indicates the best-case scenario under favorable inputs. The Mean ($\approx$ P50) \$17.29 million indicates the most likely (2P case) NPV. The standard deviation \$1.57 million shows moderate spread indicating financial uncertainty. The P90 (1P) value of \$14.80 million shows 90% chance that NPV exceeds this value.

Figure 5 shows a nearly symmetrical, slightly right-skewed. The 90% confidence interval lies between

\$14.80M (P90) and \$20.05M (P10). This shows a well-behaved economic model with a tight cluster around the mean, balanced downside and upside and a moderate range of uncertainty

3.6 Expected Monetary Value (EMV)

Figure 6 shows the EMV which combines both the NPV values and their associated probabilities (P90, P50, P10) to produce a risk-weighted economic forecast of a petroleum project.

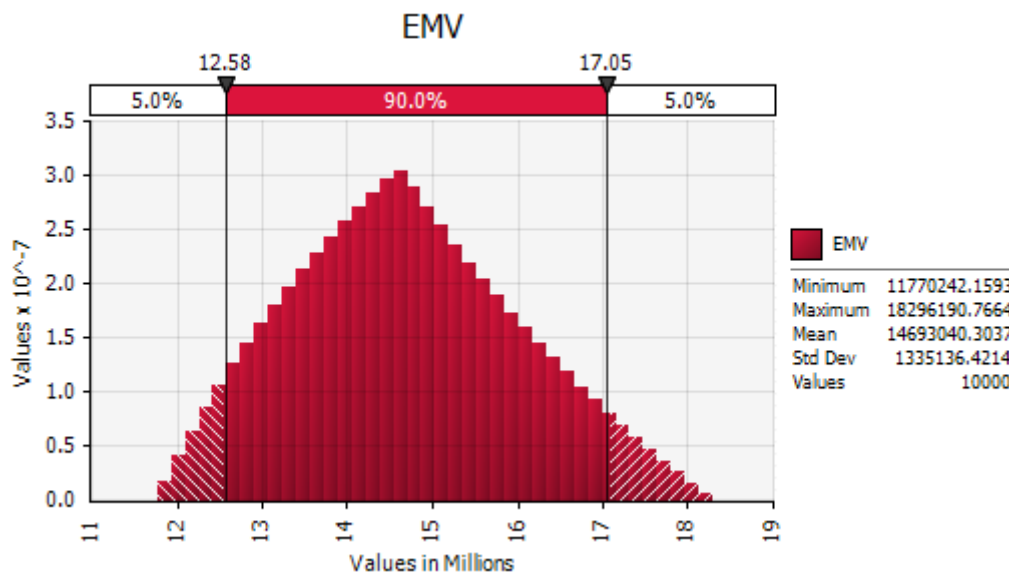


Figure 6: Expected Monetary Value (EMV)

Maximum EMV of \$18.30 million indicates the best-case scenario under optimal input conditions. Mean EMV (P50) of \$14.69 million represents the most likely project value, considering both the probability and impact of all simulated scenarios. This central value is ideal for base-case budgeting, portfolio modeling, and board-level planning. Standard deviation of \$1.33 million suggests moderate spread in EMV outcomes, implying that the project has predictable financial performance and manageable economic risk. P90 (Low Case) of \$12.58 million implies a 90% probability that EMV exceeds this value, supporting conservative decision-making, especially in financing, debt sizing, and regulatory contexts. P10 (High Case) of \$17.05 million indicates that there is only a 10% chance of exceeding this value, which reflects the optimistic, high-reward case useful for strategic planning and investor engagement. The EMV distribution appears nearly symmetrical and centered around \$14.7 million. The

90% confidence interval ranges from \$12.58M to \$17.05M, which captures the most probable economic scenarios. P90 (1P) of \$12.58 million is useful for regulatory reporting, conservative debt planning, and downside protection. P50 (Mean) of \$14.69 million is Ideal for base-case forecasting, internal planning, and mid-case portfolio optimization. P10 (3P) of \$17.05 million is Suitable for evaluating upside, capital allocation flexibility, and stakeholder communication. Unlike relying solely on deterministic NPVs, the EMV incorporates both the value and likelihood of different outcomes, offering a more intelligent and realistic view of project economics.

3.7 Sensitivity Analysis of Net Present Value Using a Tornado Diagram

The tornado diagram presented in Figure 7 illustrates the relative sensitivity of the project's Net Present

Value (NPV) to changes in the selected technical, production, and economic input variables.

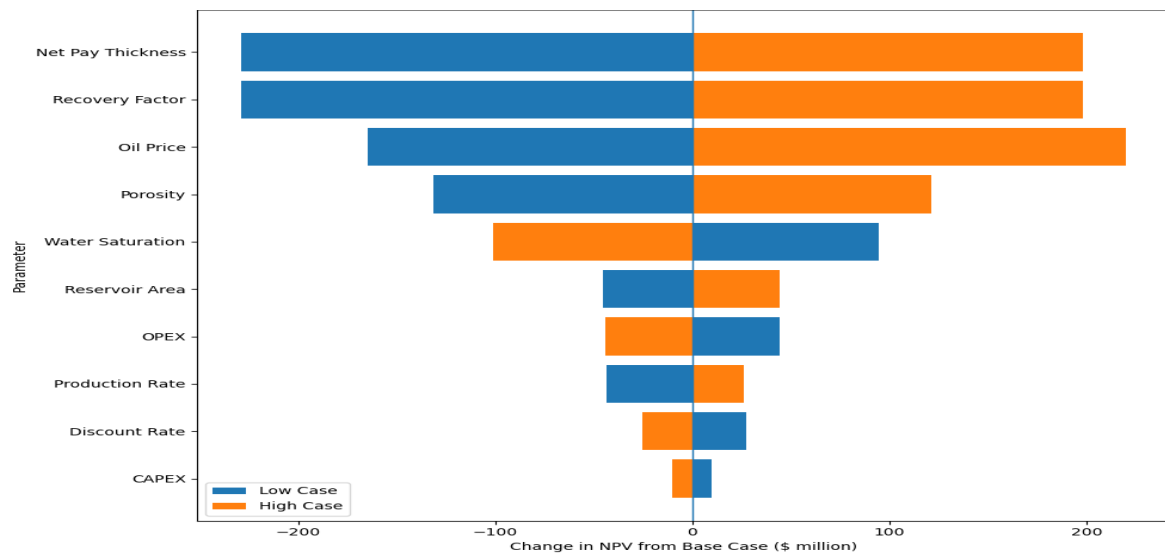


Fig. 7: Sensitivity of NPV to key variables

The resulting change in NPV was then used to rank the parameters according to their relative influence on project economic performance. The results show that oil price was the most influential individual variable affecting project NPV. The tornado bars for oil price exhibit the largest overall variation in NPV, with a low oil-price scenario producing a substantial reduction in project value and a high-price scenario generating the largest increase in NPV. An increase in oil price increases gross revenue and operating cash flow, whereas a decline reduces the economic value of the reserves and may adversely affect project profitability.

Net pay thickness and recovery factor were also identified as highly influential variables. An increase in net pay increases the hydrocarbon-bearing reservoir volume, while an increase in recovery factor increases the proportion of the original hydrocarbons that can be economically recovered. Consequently, favourable changes in either variable increase recoverable reserves, cumulative production, revenue, and ultimately NPV. The result demonstrates that variations in porosity have a considerable influence on NPV because porosity determines the available pore volume for hydrocarbon storage.

The analysis further shows that water saturation has a significant but inverse effect on NPV. Unlike oil price, net pay thickness, recovery factor, and porosity, an increase in water saturation reduces

project value. Reservoir area showed a moderate influence on NPV. Although area is an important volumetric parameter, its impact in the present analysis was lower than that of net pay thickness, recovery factor, oil price, porosity, and water saturation.

Among the operational and production variables, OPEX and production rate exhibited moderate sensitivity. An increase in OPEX reduced NPV because operating expenditure directly decreases net operating cash flow. Production rate showed a positive relationship with NPV within the model because an increase in the rate of production accelerates revenue generation and brings cash flows forward in time.

The discount rate had a relatively smaller, but still economically important, negative influence on NPV. As the discount rate increases, future cash flows are discounted more heavily, resulting in a reduction in their present value and, consequently, a lower NPV. CAPEX was the least sensitive variable within the range considered in this analysis. The tornado diagram shows that changes in capital expenditure produced the smallest variation in NPV among the evaluated parameters.

3.8 Comparison of Probabilistic and Deterministic Reserve Estimation

Table 5 shows comparison of the probabilistic and deterministic model where single fixed values were used for input parameters.

Table 5: Economic values comparison for deterministic and probabilistic model

Metric	Deterministic Model	Probabilistic Model
NPV	One value (e.g., \$13.5M)	Range: P90 = \$11.1M, Mean = \$12.96M, P10 = \$15.04M
Risk Representation	None	Captured through distribution and percentiles
Expected Monetary Value (EMV)	Not calculated	EMV = Risk-weighted expected NPV

The deterministic approach ignores the variability in inputs like oil price, CAPEX, and OPEX, providing a false sense of certainty. The probabilistic model captures the entire financial riskspectrum, enhancing planning accuracy and risk communication.

IV. CONCLUSION

The following conclusions were drawn from the results:

- Probabilistic Reserve Classification (1P, 2P, 3P) shown in the reserve distribution charts demonstrate significant variability, with wide spreads between P90 and P10.
- The distributions for Net Cash Flow, NPV, and EMV show moderately symmetrical patterns with strong mean values and manageable standard deviations. The P90-P10 ranges are relatively narrow, indicating low to moderate economic risk.
- Sensitivity outputs revealed that Discount Rate is the most influential variable on project value, followed by Oil Price, with Operating Expenditures (OPEX) having the least impact. This prioritization highlights areas where management and financial strategy should focus for risk mitigation.

REFERENCES

- [1] O. C. Adeigbe, I. F. Odedere, and O. I. Amodu, "Quantifying the uncertainty in the ultimate recoverable oil reserves using the Monte Carlo simulation techniques from 'OWA' Marginal Field, Onshore Niger Delta, Nigeria," *Geology, Geophysics and Environment*, vol. 44, no. 4, p. 401, 2018. [Geology, Geophysics and Environment](#)
- [2] Y. Cheng, Y. Wang, D. A. McVay, and W. J. Lee, "Practical application of a probabilistic approach to estimate reserves using production decline data," *SPE Economics & Management*, vol. 2, no. 1, pp. 19–31, 2010. [SPE](#)
- [3] F. Demirmen, "Reserves estimation: The challenge for the industry," Society of Petroleum Engineers, 2007.
- [4] R. S. Divi, "Probabilistic methods in petroleum resource assessment, with some examples using data from the Arabian region," *Journal of Petroleum Science and Engineering*, vol. 42, nos. 2–4, pp. 95–106, 2004. [ScienceDirect](#)
- [5] Ö. Eriçok and F. Gümrah, "Naturally fractured carbonate oil reservoir: Reserve estimation study," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 32, no. 8, pp. 697–714, 2010. [Taylor & Francis](#)
- [6] M. Galvao, L. Hastenreiter, J. Molina, A. Quadros, J. Montechiari, and S. Hamacher, "Probabilistic reserves and resources estimation: A methodology for aggregating probabilistic petroleum reserves and resources," in *SPE/EAGE European Unconventional Resources Conference and Exhibition*, 2012. [SPE](#)
- [7] B. Harrison and G. Falcone, "Are we reasonably certain that reasonable certainty adequately defines uncertainty in our reserves estimates?" in *SPE Latin America and Caribbean Petroleum Engineering Conference*, 2017. [SPE](#)
- [8] A. Jochen and S. A. Holditch, "Probabilistic reserves estimation using decline curve analysis with the bootstrap method," in *SPE Annual Technical Conference and Exhibition*, 1996.
- [9] C. Karacaer and M. Onur, "Analytical probabilistic reserve estimation by volumetric

method and aggregation of resources,” in *SPE Hydrocarbon Economics and Evaluation Symposium*, SPE-162875-MS, 2012.

- [10] R. S. Khisamov, A. F. Safarov, A. M. Kalimullin, and A. A. Dryagalkina, “Probabilistic-statistical estimation of reserves and resources according to the international classification SPE-PRMS,” *Georesursy*, vol. 20, no. 3, pp. 158–164, 2018. [Georesursy](#)
- [11] P. J. Lee, *Statistical methods for estimating petroleum resources*. Oxford University Press, 2008.
- [12] I. Mohammed, H. Abdurahman, S. D. Ibrahim, and B. M. Adamu, “Uncertainty modelling in multi-layered reserve estimation using Monte Carlo simulation,” in *SPE Nigeria Annual International Conference and Exhibition*, 2018. [SPE](#)
- [13] C. Ngu, K. F. Fozao, M. A. Onabid, L. T. Nkwanyang, and Z. Akongneh, “Uncertainty quantification in 3D static modeling: Improving reserve estimation accuracy with adaptive physics-informed Monte Carlo simulation in Y-field, Niger Delta Basin, Nigeria,” *Oil and Gas Open*, vol. 12, Art. no. 100122, 2026.
- [14] G. Quirk, M. J. Howe, and S. G. Archer, “A combined deterministic-probabilistic method of estimating undiscovered hydrocarbon resources,” *Journal of Petroleum Geology*, 2017.
- [15] P. R. Rose, *Risk analysis and management of petroleum exploration ventures (AAPG Methods in Exploration Series No. 12)*. Tulsa, OK: American Association of Petroleum Geologists, 2001.
- [16] J. H. Snow, A. G. Doré, and D. W. Dorn-Lopez, “Risk analysis and full-cycle probabilistic modelling of prospects: A prototype system developed for the Norwegian shelf,” *Norwegian Petroleum Society Special Publications*, vol. 6, pp. 153–165, 1996. [ScienceDirect](#)
- [17] M. Wallace, “Deriving proven oil reserves: Comments on the Monte Carlo simulation procedure,” *Journal of Energy Resources Technology*, vol. 11, no. 1, pp. 62–65, 1993.
- [18] P. F. Worthington, “A road map for improving the technical basis for the estimation of petroleum reserves,” *Petroleum Geoscience*, vol. 13, 2007.