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Abstract

"Decision making was never quite as easy as rationalists would have us think…. Our brains are too limited."

-Amitai Etzioni (1989)

Petroleum exploration ventures always require decision-making in the face of uncertainty. In order to evaluate prospect to support good decision-making, geoscientists must consistently assess their uncertainties for the key geological factors and estimate economic values.

As voiced by Etzioni – even the brightest experts fall prey to the human limitations and the common errors that people tend to make when pursuing complex decisions in the face of uncertainty. There is no reason to believe that petroleum geoscientists are any less prone to common cognitive limitation in their assessment of the uncertain and complex factors underlying the required assessments in prospect evaluation.

Cognitive biases often produce significant inconsistencies that lead to suboptimal exploration decisions. The central question investigated in this work is the impact of common biases on the oil and gas prospect evaluation and decision-making. We study this question by modeling and simulating the impact of the overconfidence bias and bias from trust heuristic. This allows us directly measuring the effect of the biases on the assessment of value as well as the impact on decision-making. We demonstrate that the tendency of being overconfident in our assessment of uncertainty has significant impact on the exploration decision and prospect evaluation. We also examined how the use of multiple experts can help to reduce the degree of overconfidence compared with only a single expert. Finally, we illustrate and discuss approaches for calibration and verification of uncertainty judgment. These approaches can use to help reduce the impact of biases by ensuring that experts become calibrated better in their assessments.

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List of Abbreviations

BRV Bulk Rock Volume

CDF Cumulative Density Function

E&P Exploration and Production

ENPV Expected Net Present Value

G&G Geological and Geophysics

HC Hydrocarbons

NFW New Field Wildcat

NPV Net Present Value (of success)

O&G Oil and Gas

P_c Probability of Commercial success

PDF Probability Density Function

P_e Probability of Economic success

P_g Probability of geological success

POS Probability of Success

SRI Stanford Research Institute

Chapter 1 - Introduction

In E&P companies, to perform their portfolios management and exploration decisions, they rely mainly on geoscientists' estimates. Those estimates can be classified into three main uncertainty categories: geological probability of success, probabilistic range of reserves and economic estimate of the prospect. Geoscientists assess uncertainties subjectively by their own knowledge, in other words, their brain process the information personally; it frequently leads to the deviation in probability judgment, which calls heuristics and biases. In order to make consistently unbiased estimates, people must to overcome the hidden obstacles of the human brain function.

Many scientists in social psychology and decision sciences have studied the impacts of cognitive biases, even though in the O&G upstream it is modest of researching this problem. Capen and Rose are among the first geoscientists pointed out the influences of biases and heuristics on typical geological parameters such as the reservoir thickness, the area of prospect and the HC reserves (Capen, 1976; Rose, 1987). Recently, Welsh and other also studied about the economic impacts on O&G decisions. Follow the trend, this work will investigate the impact of biases on prospect evaluation and exploration decisions for geological factors and valuation aspects, with the intention that it increases the awareness of inherent errors/biases in geoscientists' work.

Therefore, the objectives of this thesis are to:

- Summarize and clarify prevalent heuristics and biases in prospect evaluation context;
- Model and simulate the impact of overconfidence bias and bias from trust heuristic on a petroleum exploration venture;
- Present some approaches to mitigate the impact of biases and calibrate probability assessment.

Following the introduction part, the remainder of this thesis organized as

- Chapter 2 introduces definitions, descriptions and examples about the prevalent cognitive biases and heuristics in the upstream O&G industry.
- In chapter 3, the overconfidence bias will be investigated by modeling its behavior in sense of reservoir input parameters, and then calculate the outputs: net present values (NPV) and expected net present values (ENPV) – a decision criterion, to observe how decision is made under this bias.
- Chapter 4 is about the trust heuristic – the tendency and danger of using only a single expert will be discussed. We also examine of employing a small, smarter group of experts might reduce its systematic errors effect on probability judgments.
- Chapter 5 we summarize several ways of verifying and calibrating the probability assessment to improve the quality of uncertainty assessment in prospect evaluation context.
- Finally, in chapter 6 we summarize, discuss and suggest a systematic approach that can avoid biases and calibrate uncertainty assessment to help geoscientists deliver accurate geological estimates, what they promised to their companies.

The data and methods for illustration in Chapter 3 and 4 are built on and extend from the SPE 110765 paper (Welsh et al., 2007). The first step in our work will be to set a base-model that assuming biased. The second step will be to generate other models that are unbiased based on imitation bias of base-model. Our final step will be to compare and evaluate the unbiased model and the base-model (the biased one) to see how the biases behave and affect prospect evaluation and decisions.

Chapter 2 – Biases in Prospect Evaluation context

In order to decide whether to go on an exploration project, those decisions are made under highly uncertainty of geological factors; the managers require clear alternatives set of concerning prospect. Accordingly, they will calculate the values of prospect, mainly based on the input data given by geoscientists. That is, the geological uncertainty and economic assessment about the prospect.

To understand well, communicate and discuss effectively during evaluating a prospect, people require a common glossaries that usually use in the context. Because the prospect evaluation practice cross disciplinary interaction in the organization including geological and geophysical department, reservoir engineering, drilling and well, facility design and commercial section. **Table 1** lists the disciplines and their delivery products involve prospect evaluation.

Table 1 Disciplines and its delivery products in a prospect evaluation

Discipline	Delivery products
Geology & Geophysics	In place volumes, chance of success
Reservoir Engineering	Production Profile, Recoverable reserves
Drilling and Well	Design and costs
Facilities Design	Development concept and costs
Commercial Analysis	Value of the project

Look at **Table 1** we can see that the process of prospect evaluation requires participation of almost technical departments in oil and gas companies, that means the products of this section is the input for other sections. Therefore, it is necessary to have clearly common understandable, tractable and useful definition and terminologies, which are listed follow.

2.1 Prospect evaluation

It is the process and practice of measuring the worth of a particular prospect. It clarifies the alternatives for making decisions in the upstream O&G industry. In which geoscientists assess geological uncertainty of prospect and they will assign the input parameters, such as probability of success, reserves distribution, calculation of NPV of success (a function of volume, development concept), calculation of failure (G&G cost). Consequently, they will obtain the output product of process, the expected net present value (ENPV) of the project under consideration. **Figure 1** shows a simple exploration decision tree, which requires prospect evaluation's products in it. The ENPV of exploration ventures is an important parameter for the drilling portfolio, it incorporates all POS, chance of failure, recoverable reserves, investment cost and production revenues over life span of the projects, it takes into account the time-value of money.

The employment of ENPV allows geoscientists/companies ranking and selecting prospects/exploration ventures within a sedimentary basin or from different basins. Accordingly, they will only select the exploration ventures with positive ENPV; and they will choose the projects with highest ENPV to optimize their productive investment resources (capital, time, human).

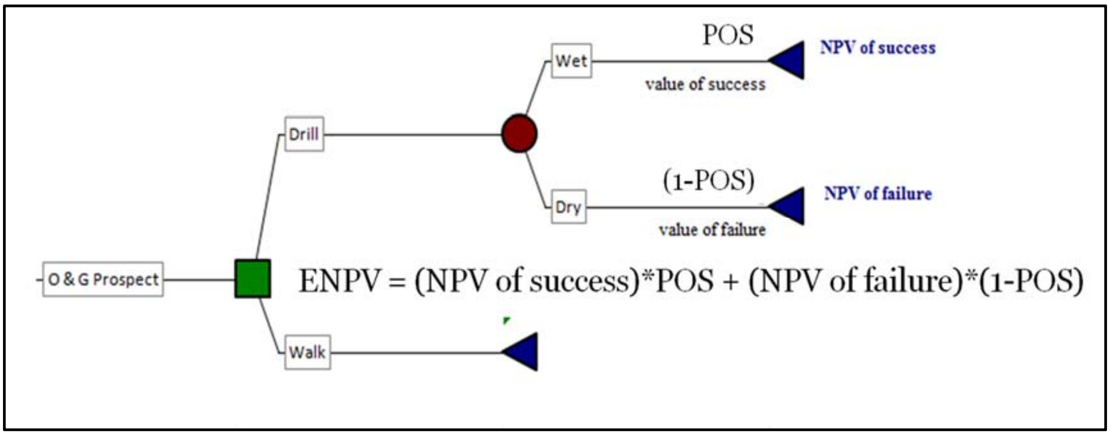

Figure 1 An exploration decision tree example

2.2 Probability of success (POS)

The POS of a prospect sometimes calls probability of discovery or probability of geological success (P_g); it is a discrete event with two-alternative (Yes-Oil and No-Dry). It expresses in numerical form, ranging in scale from zero to one. Geoscientists use POS to express their degree of belief of finding oil in a specified prospect by an exploratory well. In other words, geoscientists employ POS to quantify their own lack of knowledge about the investigated prospect (Bratvold and Begg, 2010, p. 61-63). It depends on the way of formulating and expressing, the POS can break down into from three to seven sub-factors those come from the petroleum system elements:

- *Source* relates to the probability of existing source rock, which is able to generate hydrocarbons and charge to prospect. This component can divide into smaller elements such as the presence of source and the maturity of source.
- *Reservoir* The degree of belief of reservoir units will present in the prospect. It can divide into presence of reservoir and reservoir quality.
- *Seal* is the chance of existing cap rock – prevent the hydrocarbon leaks/escapes away the prospect, which then can consider its top seal and the presence of lateral seal.
- *Trap* The capacity of keeping hydrocarbons in prospect by structuring, stratigraphic trap or combination mechanism. This element can then estimate by its closure and quality.
- *Timing/Migration* assesses the likelihood of hydrocarbon is extract from source rock and migrates into the prospect through a carrier bed, at a time after forming the trap.

Regardless of number of sub-factors using, one assumption is essential: these sub-factors are independently. Thus, the POS is a joint probability of considering components. Further to development phase, it depends on the available facilities, infrastructures and applied economic criteria of each company, the POS will be truncated to achieve commercial success (P_c) and economic success (P_e) (**Figure 2**).

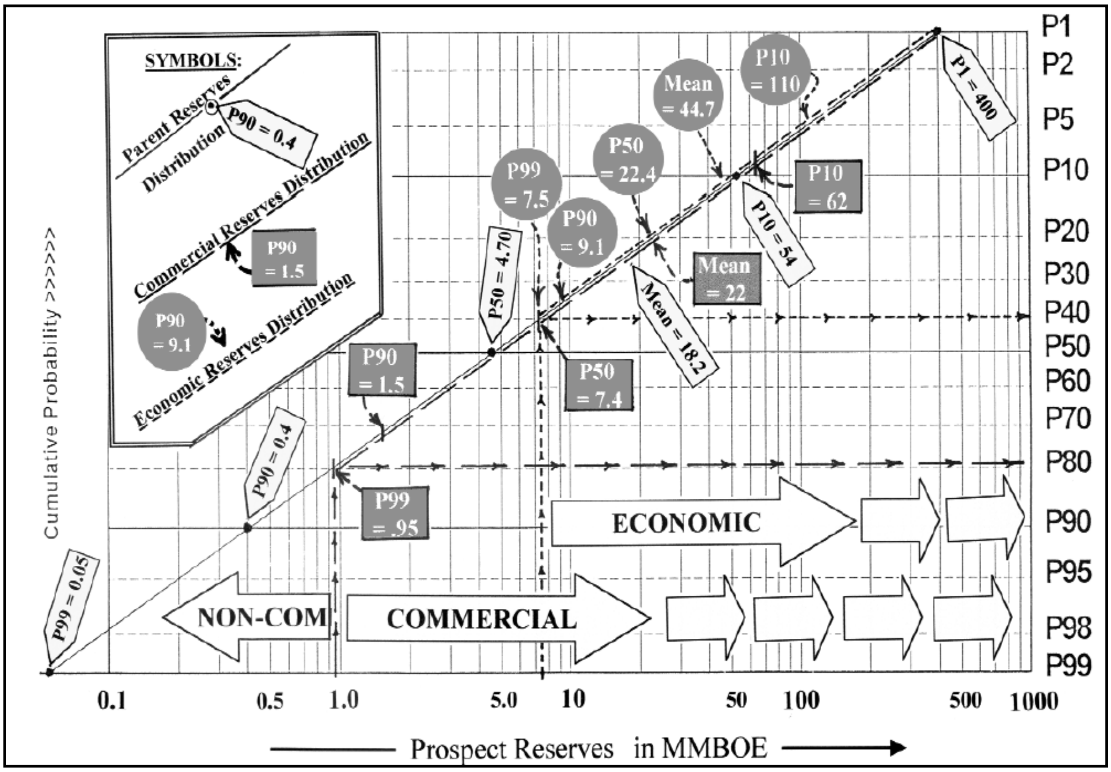

Figure 2 Truncating POS to achieve P_c and P_e (Rose, 2001)

Figure 2 shows the concept and progress that geoscientists may develop from chance of success (POS) to chance of commercial success and chance of economic success. We can see that from parent reserves distribution – corresponds to POS, technical staffs will estimate the minimum amount of required reserves of prospect to complete the well for production – corresponds to P_c. Similarly, they will estimate P_e and corresponding reserves of prospect to cover exploration cost and earn some money from P_c. Therefore, the P_e is smaller than POS, but the economic reserves will be larger.

Although geoscientists assign probability subjectively, to be good assessors, they must assure three kinds of "goodness" in probability assessments (Winkler and Murphy, 1968; Lichtenstein et al., 1980). First, the normative goodness reflects the degree to which assessments express the assessor's true beliefs and conform to the laws of probability theory. For example, if the assessor assesses chance of finding oil for a prospect is 0.3, then the chance of not finding oil in that prospect must be 0.7. Second, substantive goodness, which reflects the amount of knowledge of the topic area contained in the assessments. In our context, that reflects the knowledge of geoscientists about the prospect, the amount of information they possess. Finally, calibrating goodness, which means the objective results and predictive probabilities, must be consistent and unbiased. For example, if a geoscientist assigns 0.3 for probability of success, then the outcome should be 3 out of 10 discoveries. The post-audit HC volume should be within his estimate range of prospect volume.

2.3 Prospect volumes

Those are the amount of hydrocarbons can associate with a prospect if it discovers a producible HC accumulation. This is a continuous quantity, expresses as a range of possibilities of hydrocarbons can occur. In practice, it often expressed by a probability density distribution/function (PDF) or cumulative probability distribution (CDF) across the possible values of the volumes. However, people are not always asked to draw the entire function, the typical values are P10, P50, P90 or the mean and standard deviation of the distribution (**Figure 3**).

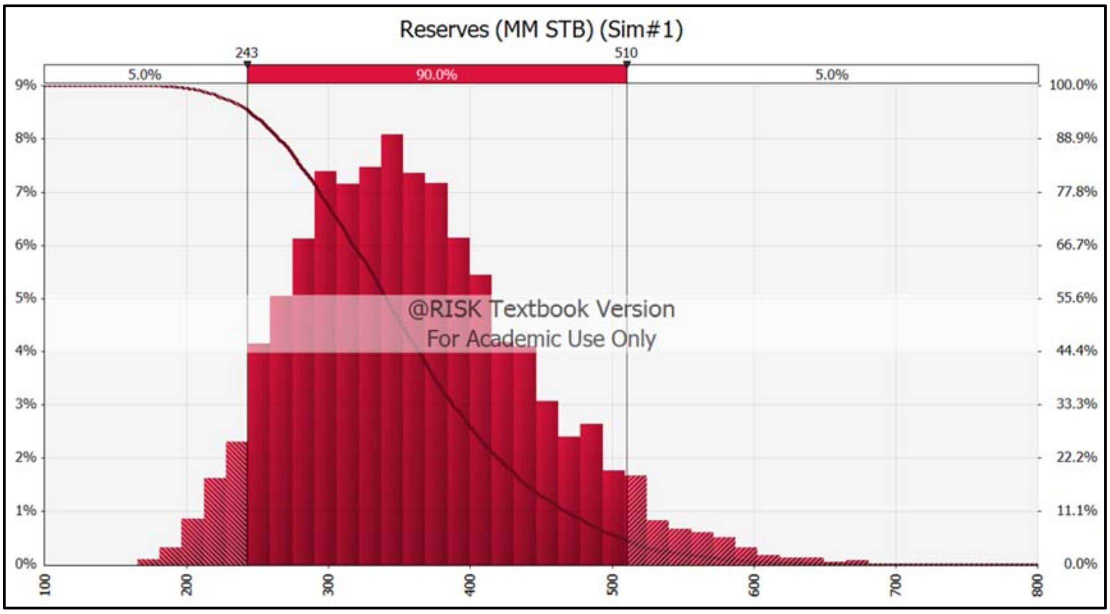

Figure 3 An example of PDF and CDF of HC volume of a prospect

Generally, it requires distinction between volumes in initial-place, reserves or estimated ultimate recovery. However, in this thesis, these terms have similar meaning; any difference will be noticed.

In the E&P industry, geoscientists employ a set of reservoir parameters, which are the results of interpreting prospect database to compute the reserves. There are some different formulas used to calculate the volume. However, due to the limitation of data in exploration stage, it requires several assumptions that are not available at the beginning of a new field wildcat prospect. Therefore, a typical formula used to determine reserve is (Rose, 2001, p.17-24)

$$\boldsymbol{Prospect\,reserve = A \times h \times R_F} \qquad (1)$$

Where,

A is productive area of prospect, in acres, hectares or kilometers^2

h is height or thickness of reservoir in feet or meters

R_F is hydrocarbon recovery factor, barrel or 1000 cubic feet per m^3/hectares-meter, or m^3 per km^2 – m.

All above described parameters taken from geological and geophysical data of the prospect by professional staffs' interpretation seismic data, studying about lithofacies, depositional environment, tectonic evolution and analog field/outcrops studies. Among constituent parameters, the first two parameters productive area and height of reservoir are the most critical; they are key impacts on prospect reserve. Whenever possible, to further stage of appraisal and development phase, the recovery factor can be break down into four smaller components: porosity, hydrocarbon saturation, and percent recovery and formation volume factor. Again, those engineering components are not always available at earlier stage of exploration. Thus, formula (1) derived to

$$\boldsymbol{Prospect\,reserve = A \times h \times \Phi \times (1 - S_w) \times R_F \times FVF} \qquad (2)$$

These geological parameters then can combine via Monte Carlo simulation to express the uncertainty of reservoir to yield a range of possible reserve (prospect - reserve distribution).

2.4 Cognitive Biases

Those are unconsciously systematic errors appear while people judge outcomes of future events in the face of uncertainty. Bias is inherent and a part of forecasting or judgment under uncertainty, whether it accounts for a large or small portion.

In general, because of the limited and natural human capacity to process information, we employ a number of principles that help to simplify the complex tasks of assessing probabilities and predicting values. Those principles called heuristics; they are routinely procedures for estimating the values, numerical quantities of a contingency, the likelihood of an event or the frequency of a class, either consciously or unconsciously. The heuristics are shortcuts that avoid extra effort of thinking, but it costs reduced accuracy of predictions and assessments.

The heuristics are very useful in simple daily life situations, but in complex environment such as the domain of petroleum exploration in which is substantial uncertainty, they lead to serious and systematic problems (Tversky and Kahneman, 1974). These problems call biases; they might be predictably or type of illusion that makes them even more difficult to overcome. The causalities are as follows:

- The tendency of substitute “questions” that is application of simple model to solve a complex matter.
- Do not updates, ignore, and omit relevant information. Alternatively, use ineffectively available information. Additionally, predict based on redundant input information.

- We often incline to rely on our intuition (unconscious heuristic) to assess and predict probability of uncertain events. This happen automatically, effectively that makes people unrealized the process.

There are some more reasons make geoscientists are vulnerable subjects of cognitive biases and heuristics:

- Their tasks are rarely repetitive to learn from the past. This characteristic makes people hard to aware of biases.
- The result for their forecasts or assessments takes quite long time to know, occasionally months or years.
- Geoscientists routinely work under business pressure, such as time, budget constraints. That leads to distract. Therefore, cognitive bias flourishes in their work.
- Their study objects – prospects are underground, they have to use indirect tools to investigate those prospect, such as seismic images, analog fields or models. In fact, there is no model or outcrop can absolutely fit the geologic nature. Therefore, there are multiple solutions for a single prospect perhaps e.g., for a sample dataset, there will be thousands of realizations in which satisfied the dataset.
- The biases lead to severe and systematic errors in making decision in the upstream O&G industry because biases of each geological parameter will be aggregated by multiplication to compute reserves. Hence, it exaggerates the problems.

The most dangerous and prevalent cognitive biases affecting judgment under uncertainty on geoscientists' work are (Rose, 2001, p.8):

1. **Overconfidence** – refers to the phenomenon of people state exceed what they know about concerning objectives, therefore, they will put forth very narrow confidence intervals about uncertainties, leading to many unexpected outcomes. Another aspect of overconfidence is

overestimates of chance of success. The more difficult the tasks, the easier people get overconfidence while making assessment.

2. **Trust heuristic** refers to the phenomenon in which people rely on single trusted information, instead of aggregating other available information. The trusted information can give by a geoscientist – an expert that manager knows him very well, and that geoscientist might have good historical performance. The trusted heuristic reflects the tendency of "chase expertise" in searching the best information, and avoid using of information that aggregated by entire geoscientists in which including some junior geologists or novices. In geologic judgment environment, the expertise is not easy to identify, moreover, an expert also is susceptible to trap by biases as non-experts as well.
3. **Representativeness** refers to a tendency that people assess the probability of an event based on the similarity or representativeness of that event with a known event. For example, geoscientists' analog based on small sample size may not be statistically; or chosen analog may not be analogous. Another example is a geoscientist can assign possibilities of a reservoir thickness based on his own interpretation of data (a prospect); he also considers that parameter in trend of statistical thickness from previous drilled prospects in the basin. However, he presumes that his prospect is much better than the base-rate frequency of the thickness in the basin. Thus, he decided to keep his own thickness judgment. That is, he already ignored the prior probability of reservoir thickness. In practice, if he is unbiased by his representative data, he should combine his interpretation and the base-rate frequency to obtain the correct posterior probability of thickness. Another consequence of the belief in representativeness is the well-known gambler's fallacy. In which people misunderstand of chance event. For example, after many dry holes in a basin, geoscientists erroneously expect that they will have wet holes -

discoveries. In fact, the chance process is separately from the sequence representativeness.

4. **Availability** – the salient, recent and unusual examples are more prone to cite and count, regardless of their real frequency in nature. That can be limited imagination, limits number of possible interpretations. An example is a geoscientist encounters oil in the granitic basement of a specific prospect – it is quite uncommon for him, because his reservoir targets are sedimentary rock normally. Therefore, when he evaluates new prospects in the basin, he always counts basement as a target without consideration of tectonic evolution or geological setting.
5. **Anchoring** this bias refers to the phenomenon of not enough adjustment in estimating, the desired iterative-reiterative process is diluted, so a low starting point leads to a lower final estimate, and a high starting point leads to a higher final estimate. Conservative estimators find difficulty in accepting the possibility of a large outcome. These are due to routinely estimates of geoscientists start from the middle of parameters, and not adjust enough to get the extremes. The assessors might unconsciously estimate objectives very similar to their references or analogs (i.e., the anchors). That leads to overly narrow confidence intervals.
6. **Motivational bias** refers to any systematic errors in attribution deriving from assessors' efforts to satisfy their own needs, rather than objectively estimate uncertainty. Consider an example, geoscientists' desire for prestige, or the need for achievement, for organization's approval. That results in skew and distortion of geoscientists' perceptions and judgments. For example, when a geoscientist really requires the prospect ventures go further (i.e., approve for a wildcat well) in order to get a promotion. Thus, he might overestimate the chance of success of that prospect, as well as its volume size. Another typical example, a geoscientist underestimates the value of a prospect

in order to preserve his prestige. Presumably, he thinks that the lower number is better than higher number exceeding the true value.

Due to time constraint, in this thesis study, we will focus on modeling the impact of overconfidence and trust heuristic on making decisions while evaluating prospect. The demonstrations will be described more detail in chapter 3 and chapter 4 of this report.

2.5 The relationship between biases

The described above biases can work separately, even more dangerous; they are relevant and can work together in an exploration venture. When they strengthen each other, exacerbate the problem (Hammond et al., 2006). Consider an example; an exploration manager might impressed by a recently dramatic venture, a huge discovery. That might anchor his own estimate and geological uncertainty assessment, and then he might unconsciously seek for confirming expert's opinion to justify his initial inclination. Unrealized the overconfidence effect, he makes a flawed decision – drill a wildcat well in that prospect. That well turns out hydrocarbon shows only. However, the manager does not want to recognize his failure, he wants to cover the sunk-cost of that well. Therefore, he continues to consider another well in the same geological trend. That is, he falls deeper into the psychological traps – the biases, he is now difficult to find a better course of action in his performance.

What is about the case of mitigating or eliminating one another of the biases? For example, each uncertain input parameter for reserves calculation assigns by different experts: a seismic interpreter estimates the area input, a petrophysicist estimates reservoir thickness, and recovery factor given by a production engineer. Finally, a geoscientist assigns POS for the prospect and gathers all information for calculating its volume. Experts have different bias in their estimate. For example, the geophysicist might be overconfident – thus, he overestimates area parameter. On the other hand, the petrophysicist might be conservatism, hence, he underestimates the reservoir thickness and the like, each pair of parameters locate opposite side of the truth. Therefore, the biases will eliminate themselves while input parameters are aggregated to calculate reserves and expected value of the prospect. This might happen if the geotechnical staffs work independently in the same database of an exploration venture.

2.6 Probability Distribution

The distribution states entirely possible outcomes and associated probabilities. It is again a subjective assessment or personal choice of geoscientists. It reflects their interpretation about geologic uncertainty in prospect evaluation context. This is a way that geoscientists quantify their lack of knowledge about study objects. For identical object, each people will assign different probability of occurrence thus specify different probability distribution to express uncertain in a model. In practice, choosing distributions to represent stochastic elements make geoscientists awkward or raise controversy. There are two categories of distribution, parametric and non-parametric distribution (Vose, 2008, p. 587-588). Parametric distribution originates from theoretical problems, its shape and range described by mathematic functions. For example, a reservoir thickness distributes as a lognormal distribution. This based on practical observations and assumptions about existing of reservoir. However, this parametric distribution forces subjective thinking of geoscientists into a hard frame in which might somewhat not reflect their opinions and unchangeable latterly. On the other hand, non-parametric distributions are more flexible; geoscientists can freely draw their own distribution based on their knowledge about the geologic objectives. In addition, they can revise the distributions when more information or data becomes available or just when they change their concepts. Accordingly, the non-parametric distributions often used to model geoscientists' opinion or their judgment of geologic probability parameters. The most common non-parametric distributions used to model parameters in prospect evaluation are uniform, relative, triangular, cumulative and discrete.

From subjective point of view, there is no “right” or “correct” probability for any uncertain event. The probability is purely expresses degree of belief of geoscientists of any uncertain event. Therefore, in this thesis, we used the triangular distribution to model for all technical parameters. It has some benefits that will discuss further on next chapter.

Chapter 3 - The effect of overconfidence bias

Capen is the first person examined the effect of overconfidence bias, he demonstrated the bias by comparing the numerical predicted values versus the actual outcomes of several technical quantities, such as thickness, area and reserves. Because technical people overestimate the precision of their own knowledge, he concluded “the errors in exploration tend to be so large” and “bias, however, can cause economic hardship” (Capen, 1976).

To systematically examine the performance and how the overconfidence behaves, we simulated the reservoir parameters influence reserves and probability of success of a project. Of each parameter, the base-case would regard as overconfidence; the other with wider range is the unbiased one, which generated from the base-case by adjusting equal amount on each side of the distribution.

The reasons why we prefer triangular distribution to model input parameters that used determining the reserve instead of other distributions such as lognormal or normal distributions (envelop method) because it is simple, more important we can interpret by visualizing overconfident effects and it is widely used in oil and gas industry. Therefore, once we are skilled practice on it, we can investigate with other type of distributions.

3.1 Data description

In order to simulate the influence of overconfidence on upstream oil and gas decisions, we used a data set of an offshore development project. The values of input parameters used in base-case showed in **Table 2**. They defined by triangular distributions. Additionally, the probability of success (POS) for this prospect assigned to be 0.3 as often seeing for a low-risk project. This POS will vary associated with reserve size of prospects, which will present more detail later.

Table 2 Input reservoir parameters of base-case model

	Min	Mode	Max
Area (acres)	15000	17500	20000
Thickness (ft)	115	150	215
Porosity (%)	18	20	25
Water Saturation (%)	30	35	45
Net / Gross	0.6	0.7	0.8
Formation Volume Factor	1.15	1.2	1.3
Recovery Factor (%)	15	20	30

Other engineering input parameters to transform reserves to economic metrics, such as number of wells, capacity limits, development schedule, and pressure depletion, decline rate and so forth were determined interplay reasonable with the reserve size/reservoir model.

The economic factors oil price, facility cost and the like were also treated deterministically to simplify scope of works.

3.2 Methods

In the upstream oil and gas, the most widely confidence interval often used is 80%, which defines by a pair of extreme P10 and P90. Therefore, in our model of overconfident impact has done by calculating the 10^{th} and 90^{th} percentiles of each parameter base distributions. Next, the unbiased (wider) distribution was generated by adding these two values by an equal amount. Thus, the new distribution will have identical values, served as other percentiles, for example, 20^{th} and 80^{th} or 25^{th} and 75^{th}– **Figure 4** and **Figure 5** show this. Herein, the wider distribution would regarded as the truth or real versus the narrower – overconfidence distribution. The more overconfident degree of base-case, the wider distributions are on the unbiased distribution.

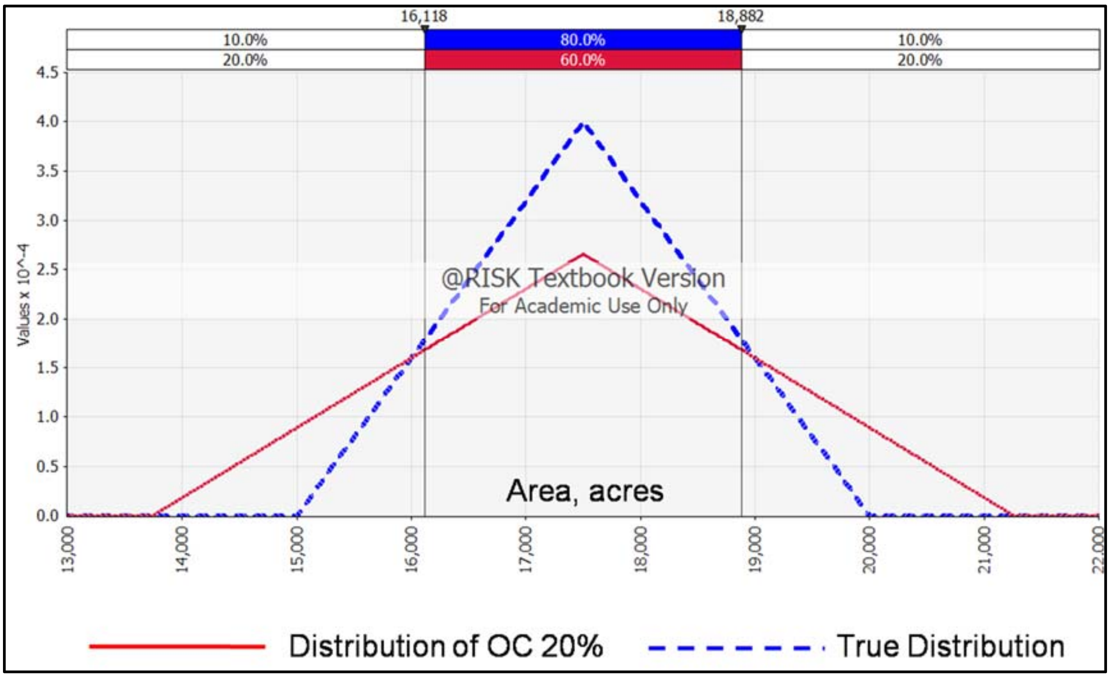

Figure 4 PDF's transformation of 20% Overconfidence case

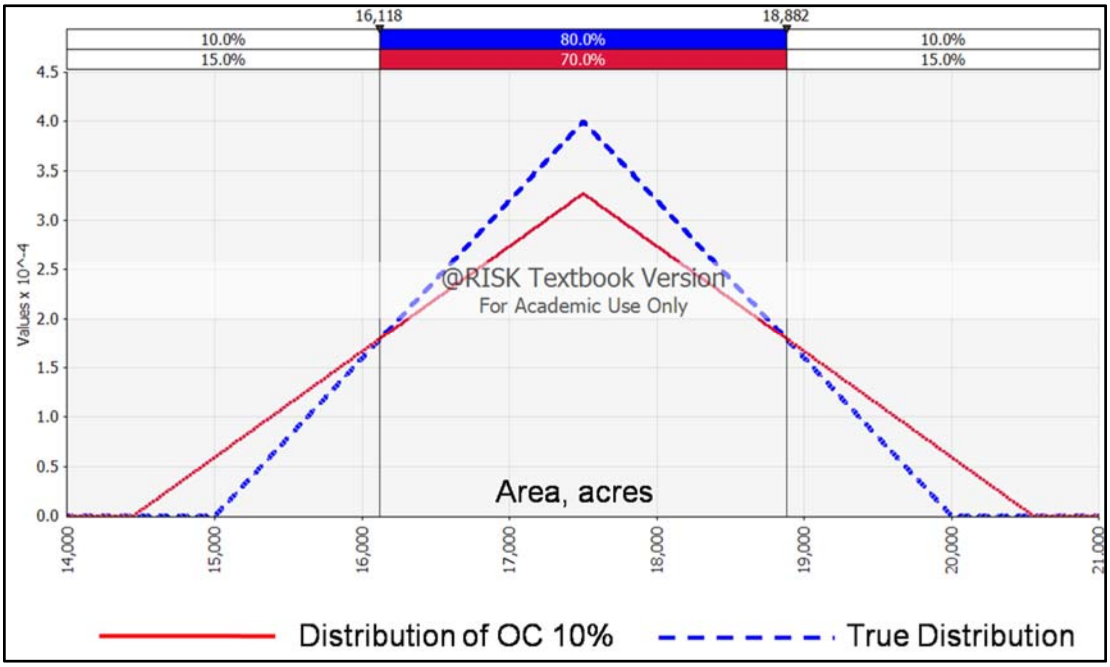

Figure 5 PDF's transformation of 10% overconfidence case

Look at **Figure 4**-the illustration for overconfidence impact on area parameter. One can clearly see that the overconfidence distribution only covered 60% confidence interval, but people stated that it was 80% confidence interval. Thus, in fact, they are overconfident by 20%.

Similarly, **Figure 5** shows at 10% overconfidence degree, the given distribution by a geoscientist captured only 70% of the truth distribution.

The method applied for the rest parameters in **Table 2**. Next step, these distributions are combined to create a model of calculating prospect reserves, using formula (2). This model then runs for seven cases: the base-case and six degrees of overconfidence (from 5% to 30% with 5% increments). Here, the core assumption is the base-case represents for the overconfident value given by a geoscientist; the other six cases are the one not overconfident – represent for the truth values should be.

Then, using each mean value of reserves, and capital expenses and operation expenses values appropriate to prospect size for each case to calculate the NPV of project.

The NPV of failure of project is cost of geological and geophysics (G&G) study, seismic cost and well cost was also taken deterministically, with consideration of location on the world, onshore versus offshore. For example, drilling cost in offshore NCS can be range from $70 million to $200 million. However, if it would drill onshore Central Asia, the cost might be lower by ranging from $15 million to $25 million. Associated with well cost, the prospects in offshore Norwegian continental shelf might be much bigger in size to assure economic standard for drilling, compare to prospect size in Central Asia.

To calculate the ENPV of project, a simple overconfident model for POS has made as follows: by assuming, the POS of base-case is 0.3. Because overconfidence makes people overestimate the chance of success, therefore, the "real" value of POS should be lower (**Table 3**). Accordingly, the "real" POS are adjusting by decreasing 5% increments from 0% to 30% overconfidence degree.

Table 3 Overconfidence degree on POS

OC degree	0%	5%	10%	15%	20%	25%	30%
POS	0.3	0.285	0.27	0.255	0.24	0.225	0.21

3.3 Results

Figure 6 shows the result of 10000-iteration simulation for each level of overconfidence impacts NPV value of the modeled project. The simulation performs on seven degree of overconfidence, from 0% to 30% with 5% increment.

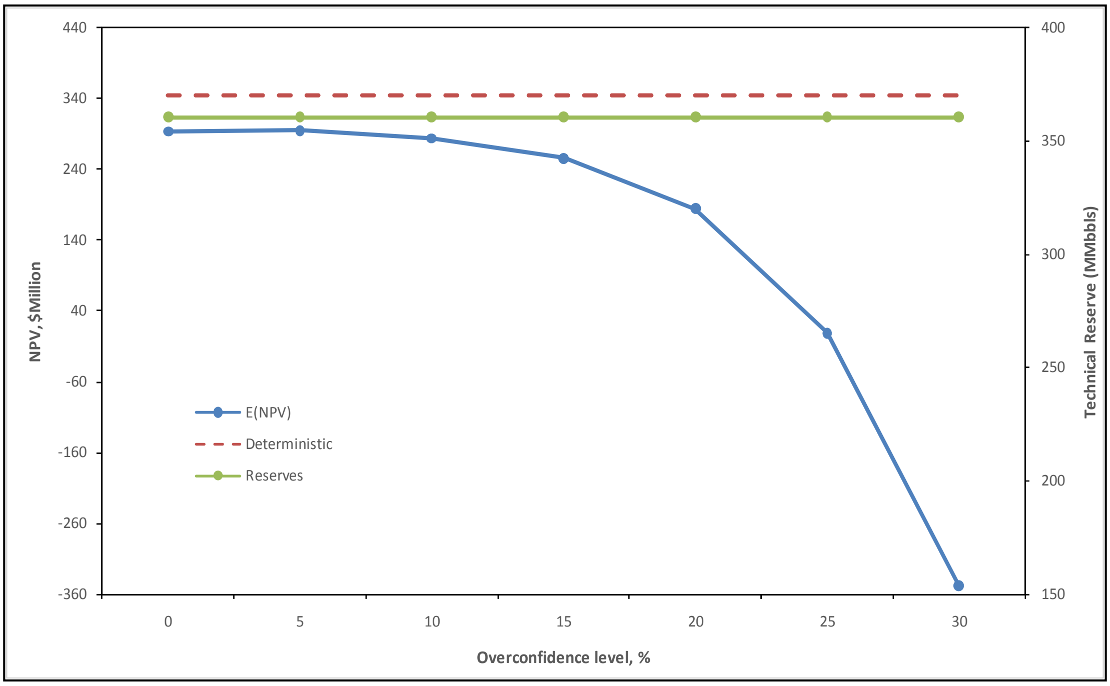

Figure 6 The impact of Overconfidence on NPV of success

In every case, if we use deterministic method to calculate the expected value of the project, we will get a steady number remaining at approximately $340 million. Similarly, the technical reserves will be about 360 million barrels. The actual reserve is a function of economics would change accordingly.

However, the simulation results do not reach the expected value of the project. Even at 0% overconfidence level – the geoscientist is not bias, the project NPV value is only $290 million. The different result is due to non-linearity relationship between parameters of the model. This gives another obvious evidence for the argument of "do not expected on the expected value" and the need to use probabilistic instead of deterministic calculations when estimating the expected value of important and complex projects.

Figure 6 shows the declining trend of expected NPV values as the level of overconfidence increase. With 5% overconfidence, the expected NPV is almost equal NPV of no confidence case. It means that, if geoscientists are slightly overconfident (up to 5%), then there is no effect on the NPV. However, with 10% overconfidence the real value of the project is $280 million, compared to the $290 million that given by geoscientists' parameters input. The decline trend of NPV continues until the overconfidence level reaches 30%; the NPV dramatically dropped to -$350 million. This means, if geoscientists were 30% overconfident relative to the truth of uncertainty, they would estimate the NPV of the project is $290 million whereas, in fact, the real NPV is $640 million below that value. In addition, if a company used a deterministic approach with the mean – expected values of the input parameters would estimate the value at $280 million, $630 million higher than the true NPV.

Figure 7 shows the effect of different degree of overconfidence made on the ENPV of the project. Herein, the ENPV consisted of failure cost of the project, if the ENPV is positive then the decision is on, otherwise it is off. Look at **Figure 7** one can see that, the estimates given by a geoscientist with overconfidence bias are always yield positive ENPV, while, the truth is negative even with 5% degree of overconfidence only. At the 5% overconfidence case, the NPV of success is almost equal to NPV of non-overconfidence. However, the ENPV is negative because the overconfidence also has effect on the POS – make it higher. Therefore, the true value of ENPV is negative versus the positive ENPV of 5% overconfidence.

The trending of negative ENPV value of overconfidence cases are very clearly in case of 15% overconfidence and more. This trend is even much more clearly, if the cost of failure is higher.

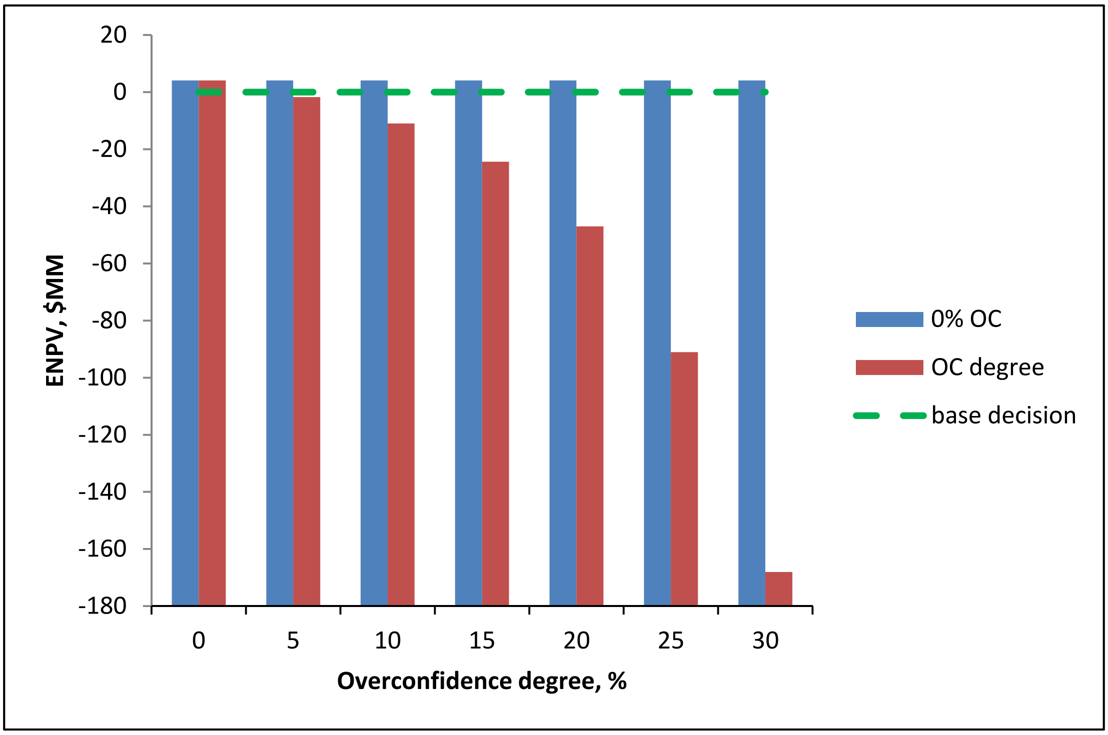

Figure 7 The impact of overconfidence on ENPV

3.4 Discussion

The above results of the overconfidence model clearly point out the impact of overconfidence bias must be acknowledged and mitigated necessarily. The overconfidence model applied to the POS and reserves calculation - not to consider the effect might have on economic parameters and G&G costs, at all level, lead to overestimating the NPV of success of the project. Except the 5% overconfidence case, the NPV of the project is almost non-impact, approximately $290 million. Nevertheless, in every case resulted in the overestimation of ENPV of the project – a direct decision metric.

The commonly extent of overconfidence degree expressed by people in test of the bias was about 30% (Capen, 1976). In the modeled project, at this level of overconfidence, they will overestimate the NPV an amount of $640 million. Additionally, they estimated a negative ENPV as a positive ENPV. Therefore, a company would decide to go ahead with the project whereas it must stay away. It means that they would make bad decisions that damage their business; with a loss of $350 million, it might be irreparably.

Chapter 4 -The impact of Trust Heuristic

The trust heuristic refers to the tendency to rely on the information sources in a particular strategy that agrees to managers' belief or perspectives. In some sense, the information sources, here, can understand are the experts' opinion, or different types of data about the prospects, such as seismic data, logging data, core data and drilling data, etc. The tendency to select and rely on the individual expert's opinion, would regarded as the managers or decision makers overly trusted on the best expert's opinion and/or agreed with the way that expert interpreted data, and his expertise professional. The reasons underpinning that reliance can be drawn from historical outperformance of the expert or just expert's confidence in considering the current prospect. However, in probabilistic and unpredictable environment as the upstream O&G industry, there are two big problems with relying on a single source of information. The first is that true expert is extremely hard to identify (Capen, 1995). In fact, managers might be astray by ill-defined cues for expertise. Those are the expression of confidence, talkativeness, and the amount of information an expert possesses (Mannes et al., 2014). The second, and more serious, even the most intelligent expert has biases and blind spots in his main field (Surowiecki, 2005, p.278). Thus, he does not know where and when he might make mistakes while rendering his opinion and probability judgments in an uncertainty environment.

Therefore, whatever reason, this should not be the case. The decision makers or managers should rely on collective judgments to achieve the virtues of crowds. Moreover, in oil and gas exploration upstream, at the initial stage, information is often sparse and unconnected with each other, thus, we should combine all the information available after filtering poor quality one. Rather than trusted in particular information source or any single individual expert. **Figure 8** shows reasons why we should incorporate experts' opinion, better than trust on an expert.

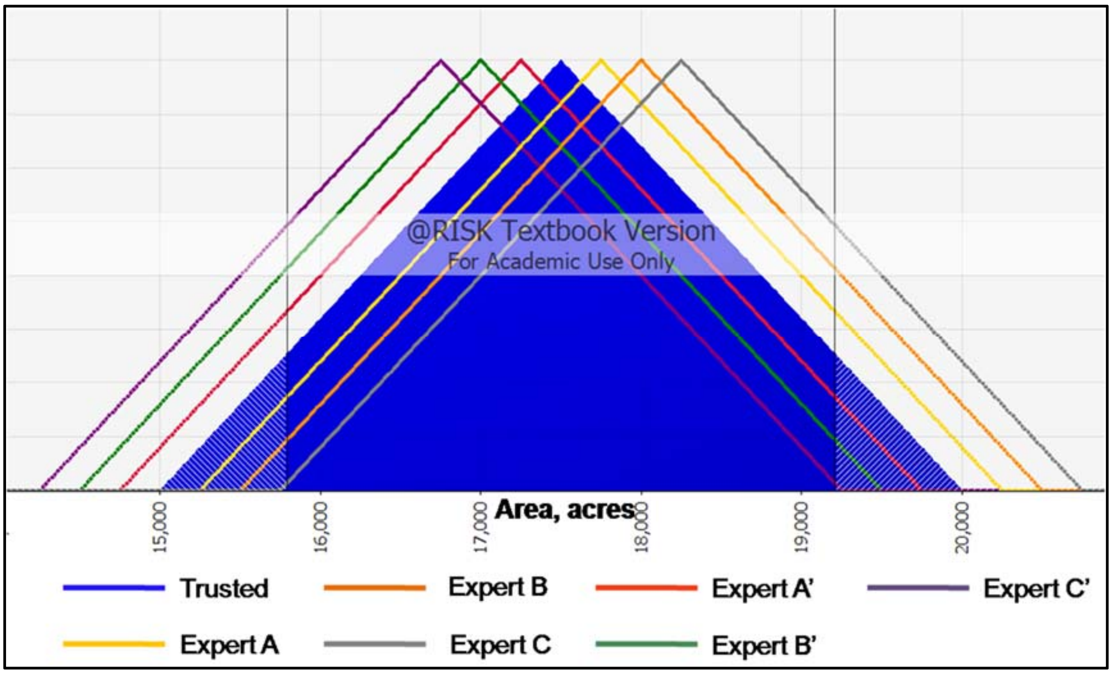

Figure 8 Independence Expert Opinions

Figure 8 shows the beliefs of seven experts on the uncertain of area parameter. The trusted expert's opinion is the distribution in the center of the figure. In practice, each expert might give different type of distribution. For simplicity, in the model all seven experts give the same type of triangular distribution. The other experts' distributions have identical range with the trusted expert, but the modes are different. Furthermore, **Figure 8** shows the independent experts' opinion, that is, the other experts' beliefs do not depend on the trusted expert. Therefore, their distributions are spread out (on both sides) of trusted expert's distribution.

If the experts are dependent, their opinion will locate on a side of trusted expert. The reason might be the trusted expert's opinion influences other experts. Alternatively, the other experts might imitate the trusted expert's opinion. **Figure 9** shows the dependent experts' opinion – they all believe that the area parameter might have low value. On the other hand, **Figure 10** shows the dependent experts' opinion with estimating area might take high value. Even dependence, if the manager would use an aggregated opinion, he still get the benefit of reducing overconfidence bias of individuals.

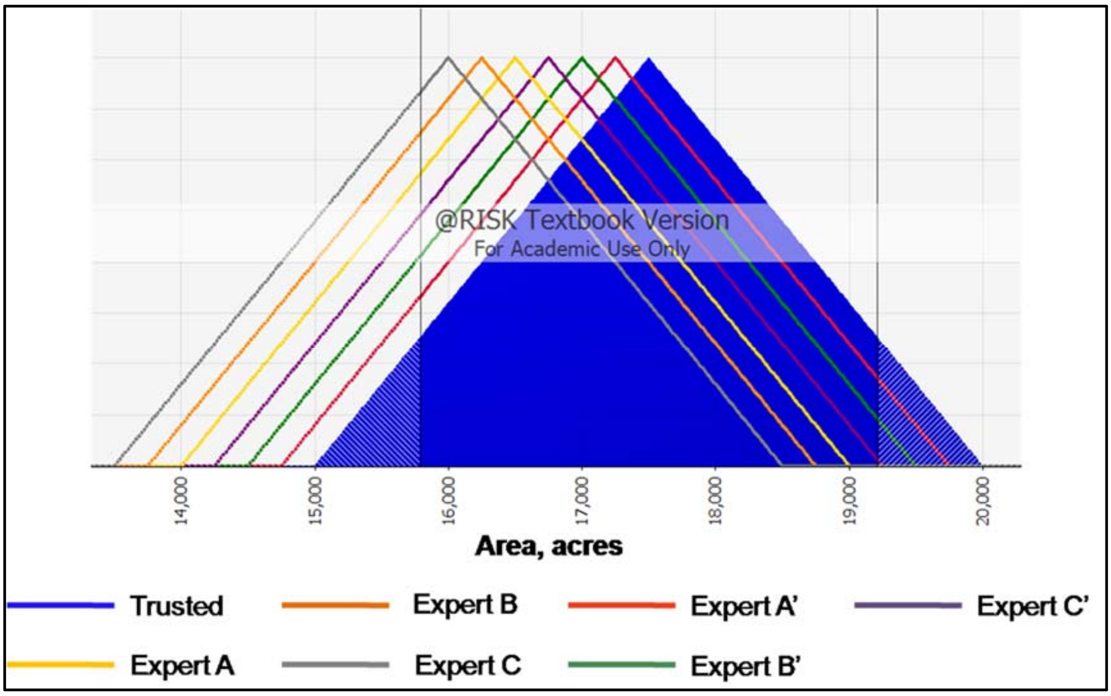

Figure 9 Dependence Experts' opinions - low values

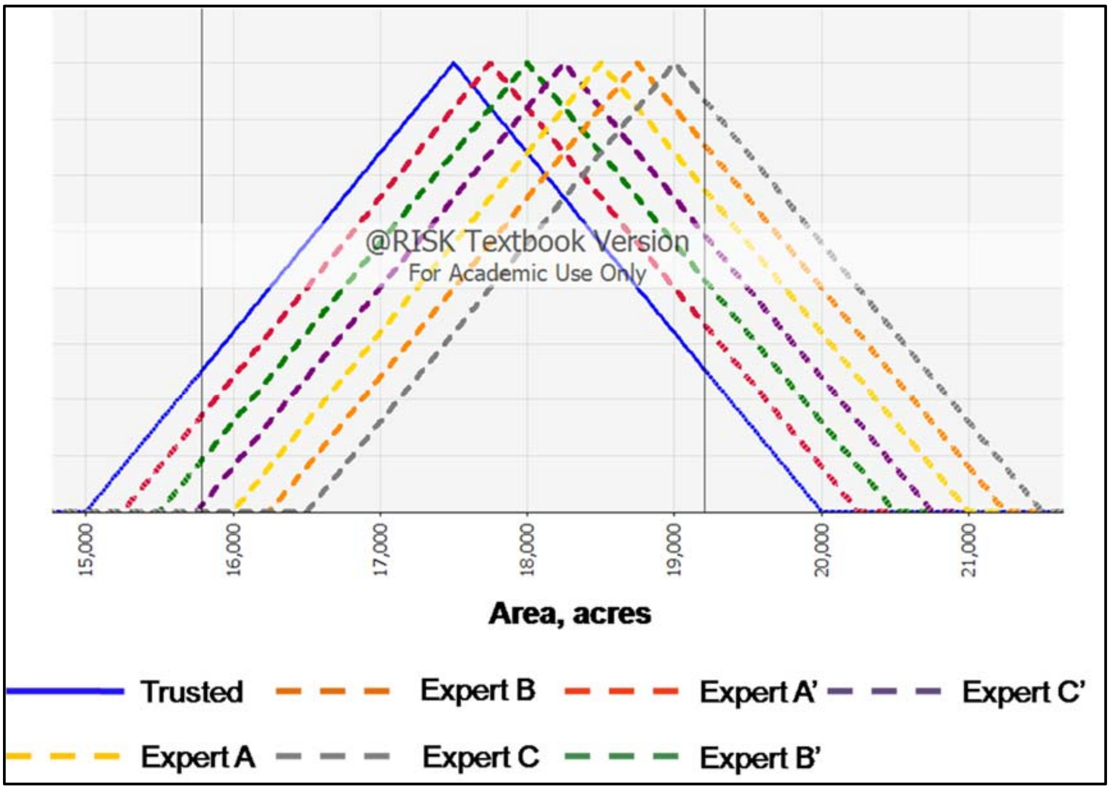

Figure 10 Dependence Experts' opinions - high values

The consensus of experts may harm the role of aggregating opinion. If the experts agree on each other ideas (distribution), the diversity of environment will decrease. In other words, the phenomenon will not widen distribution sufficient to eliminate the overconfidence degree of individuals.

When it comes to experts' opinions aggregation, there are two ways: behavioral aggregation and mathematical aggregation. In behavioral aggregation, the experts are directly or indirectly discussed their opinions, and suggest a final judgment. Mathematical aggregation can be using techniques of Bayesian to update in succession each expert opinion by multiplicative rule; or using simple equally weighted for all expert members (Clemen and Winkler, 2007). In either ways, as long as the diversity and the independence of experts are kept good enough, the advantages of collective judgments will be present. That is, the errors due to biases made by individual members will effectively cancel out themselves, leaving the useful knowledge that group members occupy.

As discussion in chapter 3, people are universally overconfident when rendering the range of distribution of any uncertain input parameters might take. We will demonstrate that aggregated distributions act to reduce the impact of overconfidence of a single individual expert. Herein, the reality should be wider than the interval given by the trusted expert.

4.1 Methods

The subjective probability distribution of trusted expert was modeled as a triangular distribution – **Table 2**, described in chapter 3. The modes of the other experts' distributions were calculated by averaging its minima and maxima[1]. The range of other experts is identical as the trusted expert's range. The other experts' distributions are then generated by shifting the trusted expert's distribution to the left or right its initial location.

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[1] We examined several ways of generating the mode of other experts by taking their modes randomly from normal distribution in which the mean is trusted expert's mode, and the standard deviation is the difference between the trusted expert and other experts. Another way of drawing the other experts' mode is from a uniform distribution (minimum, maximum). Either method, we just consider the range of combined experts' distribution, which should be wider than trusted expert's distribution.

All seven available experts' distributions or sources of information combined into aggregation triangular distributions by taking the smallest minimum value; the mode is average of the modes; and the largest maximum value from the set of triangular distributions. By combining experts' opinion, **Figure 11** shows that we can reduce the overconfidence of trusted expert.

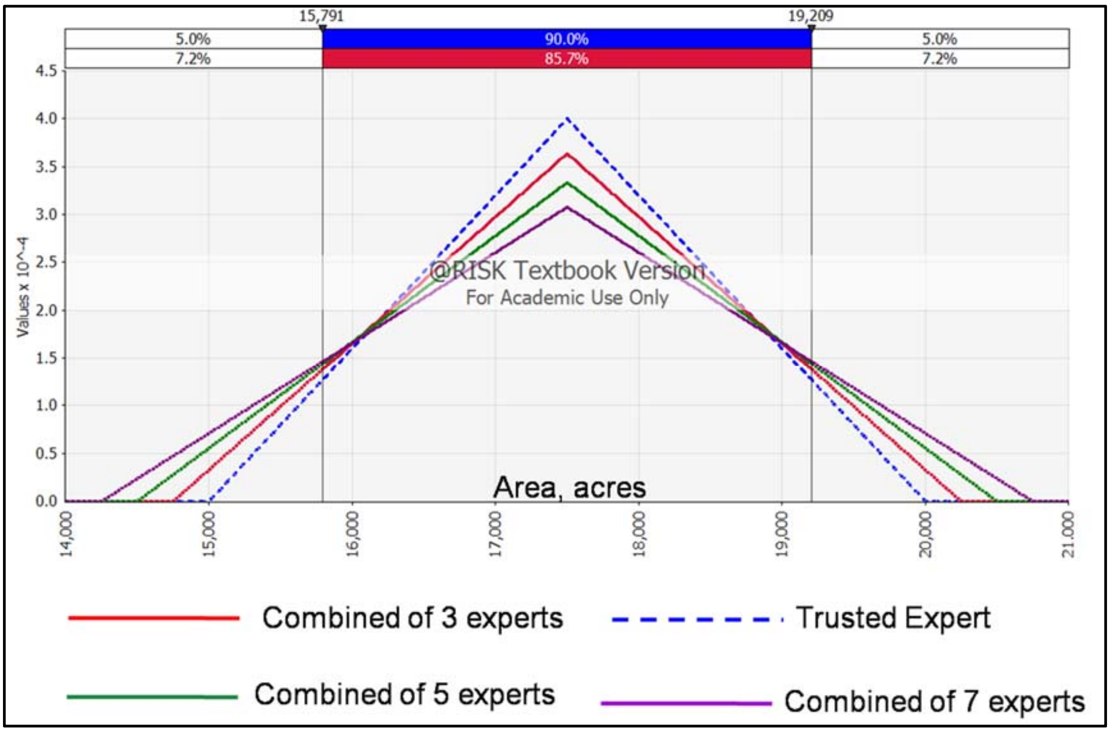

Figure 11 Single trusted Expert versus Combined Expert Opinions

The way of combining experts' opinion above is quick, simple and intuitively. In this situation, we only consider ranges of the distributions – it means that we only pay attention for extreme values. Furthermore, according to **Figure 11,** the mode and the mean of combination distribution will not vary too much. This might affect the NPV values, since we calculate it by sampling the whole distribution, but not only the extremes.

By comparing the 10^{th} and 90^{th} percentiles of the trusted expert's distribution to the aggregation distribution, the amount of reducing overconfidence can be determined (**Figure 12**).

Next, the modeled parameters of trusted expert and combined experts' opinion used in calculating the reserves and the NPV for each of the trusted expert's model and six levels of combination: from 2 experts to 7 experts.

4.2 Results

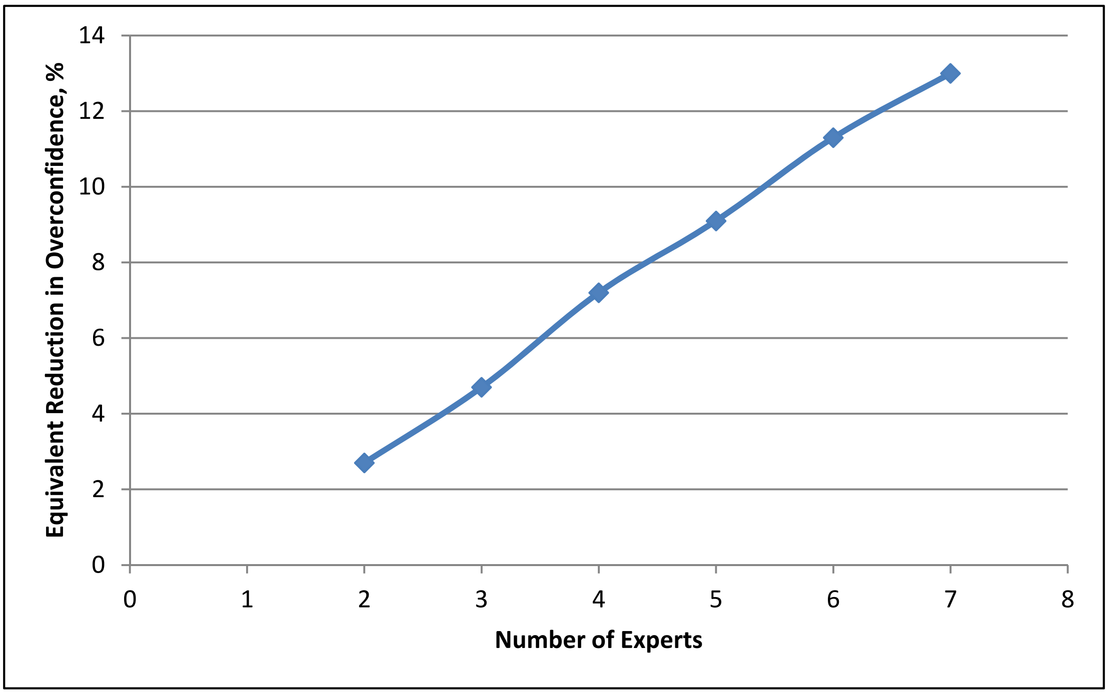

Figure 12 Overconfidence reduced by combination number of experts

By incorporating three experts, the equivalent reduction in overconfidence is about 5% (**Figure 12**). Moreover, the amount of overconfidence reduction increases as the number of experts adding more, combined seven experts' opinion will reduce overconfidence up to an approximate amount of 13%.

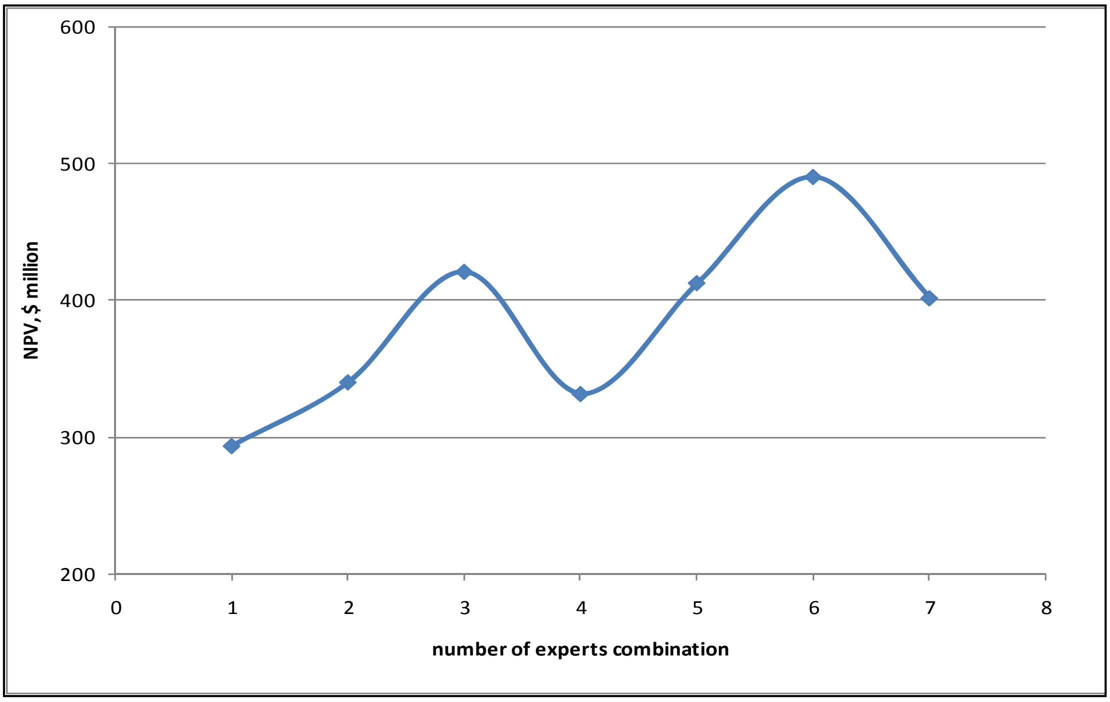

Figure 13 Trusted Expert versus Combined Experts' NPV

Figure 13 shows the results NPV of varying number of experts' opinion aggregation of the project. That is, the mean NPV from the 10000-iteration simulation for each case. Unlikely the trend of reducing overconfidence degree while combining more experts, the NPV values are fluctuated: starting with around $290 million of trusted expert, it increases up to around $420 million – combined three experts. Next, it decreases to approximately $340 million – NPV of combining four experts; and then it goes up again, reaches the pick of almost $500 million – NPV of combined six experts. Finally, it goes down to $400 million while combining seven experts.

4.3 Discussion

On the one hand, we demonstrated of combining multiple experts, which will reduce overconfidence degree of an individual expert.

On the other hand, the result of NPV calculation conflicts with our overconfidence model described in chapter 3. Even though the trusted expert was modeled overconfidence, but he underestimated the NPV comparatively to other experts' estimates (as we assumed the wider distribution reflects the truth). The reason might be the means of aggregation experts' opinion and trusted expert's opinions are not vary too much[2]. In addition, it might be our experts' distribution does not include characteristics of diversity/dispersion in expertise significantly and bracketing of the judgmental environment. Since we only consider reducing the overconfidence degree of the trusted expert.

[2]We examined the Vosecombined function, which combines experts' opinion by averaging each percentile of subjective distributions instead of only averaging the modes-as our method. However, the result of NPV calculation is almost identical, even though the means and the modes vary more intensively.

Chapter 5 - Calibrating probability assessment

In order to make good decisions in the upstream oil and gas industry, geoscientists require providing well-calibrated probability assessments for using in prospect evaluation; those are probability of success, prospect reserves sizes and the economic estimates of the project.

Given the fact that people are susceptible subjects to be trapped by the dangers of biases, it seems that no one can present a consistent probability judgment for making good decisions. Fortunately, there are several approaches suggested to overcome that difficulty. In this report, we summarize briefly the approaches of calibration probability assessment.

5.1 Rose's recommendations

Rose (Rose, 2001, p. 13-15) recommended a series of strategies that has applied in the O&G Companies **(Table 4).**

Table 4 Methods to improve accuracy in uncertainty judgment (Rose, 2001)

Number	Techniques
1	Use of geotechnical models as analogs
2	Use of multiple working hypotheses and maps
3	Independent multiple estimates
4	"Nature's envelopes"
5	"Reality checks"
6	Proper statistical procedures
7	Practice and comparison of prior predictions with outcomes

Geotechnical analog models there are three types of analogous models used to forecast newly prospects by using the well-known prospect models data. The first common analog model is stratigraphic model, which is a model of depositional environment, sequence stratigraphy of an outcrop or developed field. From that, geoscientists can understand, interpret the concerning prospect about its size, reservoir characteristics, trap types, source rock quality and quantity, oil and gas migration pathways, and the like. Even though, there is very little data exist at the early stage of exploration. Other common models for analogy are structural model and facies modeling. These two models help geoscientists understand and insightful forecast about reservoir behavior. Additionally, geoscientists also often use analogous economic model for new prospect, given the fact of available technical data and market trends.

However, the analogous models can lead to anchoring bias; it means that geoscientists do not adjust sufficiently for new prospects. Therefore, while using analog models, people require keeping an open mind, flexibility in analyzing, interpreting new prospects based on analog the previous models.

Multiple working hypotheses and maps in practical exploration activities, geoscientists must to examine several hypotheses of geologic matters (tectonic evolution, basin evolution, geological setting, etc.) for a set of data (seismic cube, nearby wells) and construct, evaluate the alternatives interpretation products. For example, for the same data set but different interpreters with their own concepts will make several different structural maps, or various depositional interpretations. In addition, each interpreter also delivers several possible maps of prospect parameters, which shows optimistic (P90), intermediate (P50), and pessimistic possible cases (P10).

Independent multiple estimates this strategy refers to "the wisdom of crowds". That is when people judge under uncertainty, the estimate and assessment of a parameter given by considering and consensus of multiple sources, that are generally less biased and more realistic than the result given by a single assessor. In practice, modern oil companies achieve this by organizing their structure, such as multidisciplinary exploration teams – combination of multiple disciplines within a company (geology and geophysics, drilling and development, commercial), peer review of new projects, final review a prospect by a senior risk management committee, or estimating procedures “Delphi Rounds”. A common practical way is to form exploration joint ventures, which participates by several companies. In which, technical ideas will be discussed through subcommittees to find optimal estimates.

Nature’s envelopes it is a strategy of applying historical observations of geological distribution parameters for estimating new parameter input. For example, we observed that the bulk rock volume (BRV) of known prospects distributed lognormal, and then we apply this natural define for estimating BRV of a new prospect. Even though, the new data might not distribute lognormal, but many software enable “fit” the data to lognormal distribution. This process honors the data and constrain by expected natural parameters. However, using nature’s envelopes raises controversy that assigning distributions and estimating parameters input are subjectivity; especially, at very early stage of exploration, we even do not know whether existing of such parameters. Recently, several major oil companies report the accuracy improvement of using this strategy (Brown et al., 2000). Another natural envelope is quantified possible ranges of parameters. For instance, range of hydrocarbon recovery factor is approximately from 50 barrels per acre-foot to 1200 barrels per acre-foot. Thus, based on data of new prospect, the estimator can assess hydrocarbon recovery factor within that interval.

Reality checks after achieving preliminary estimates about prospect, the results should be repeatedly compared against known examples for obtaining reasonable parameters. The common objects used for reality checks are field size distributions (FSDs), historical drilling record, and worldwide databases. By comparing parameters of new prospect against the one in analogous prospect in the same trend, or basin might help for practical adjustments, such as reserves size, chance of success, etc.

Proper statistical procedures prospect parameters often estimated by 80% confidence range, from low side (P90%) to high-side (P10%) cases. Within that range, the values of average or median parameter should be paid more attention, because over long - run the expected outcome of prospect is the mean value of reserves case and it often used to evaluate economic factors of the exploration ventures.

Practice and comparison of prior predictions with outcomes by keeping continuously record of the outcomes versus the estimates of prospects, this provides learning lessons for individual geoscientist, exploration team and oil company. Normally, after a drilling campaign or just a drilled well, company will ask for evaluating result of that well whether its success or failure. Accordingly, people will discuss, clarify and improve the quality of their probability assessment and estimate for future prospects. This strategy requires systematic gathering information procedure to have adequate samples. It also requires openly and encourages discussion among technical staffs and managers for assessment quality, but not for threatening career.

In fact, it depends on the project and its policy; each company might apply and combine above techniques differently.

5.2 The Stanford University/Stanford Research Institute (SRI) approach

To assess effectively probability of uncertain events, people can decompose the task by two main components: the first step is definition all the possible outcomes of the event, the second is assignment of probabilities to those outcomes. This process is called elicitation. The SRI approach shapes structured probability elicitation, as it goes from very early to the end of the elicitation process. Thus, it can help geoscientists to avoid being trapped by biases.

Ideally, the process is conducted through interviewing and communicating between an elicitor/analyst, who is a professional in probability elicitation and a geoscientist, who is evaluating prospect. Otherwise, geoscientist should be trained and adapt to follow the process. This elicitation process includes five main steps.

1. Motivating: explain the task and understand its importance, aware of motivational biases at this step. For example, the geoscientist desires the project will go further to gain a promotion; therefore, he might overestimate the value of prospect. Alternatively, he was success in the past, and now he wants to protect his prestige by underestimates the value of project, by means that given a lower number is better than higher number whatever the consequence of the prospect. The other common bias at this step is confirmation bias, that is geoscientist presents his opinion which conforms to his manager's expectation instead of giving an honest opinion – reflects his knowledge about studying object.
2. Structuring: this step is for making assumptions to define structural uncertain events, and its elements. For instance, in exploration phase, the uncertain event is drill a wildcat well in a considering prospect; and the assumption is there is a considerable amount of oil in that prospect.
3. Conditioning: this step is for clarifying how the geoscientist makes probability assessments plausibly. Normally, the geoscientist will make probabilistic judgment by interpreting geological data, considering all relevant subsurface geological evidence, as well as data quality and quantity. In addition, he also considers general geological setting of sedimentary basin or trend, in which his prospect located. The common biases feature in this step is anchoring, availability, and representativeness. This requires effective techniques to counteract their impacts. For example, to avoid geoscientist's

representativeness and optimism biases on his estimate about prospect's volume, elicitor can remind him about field size distribution in the basin.

4. Encoding: at this step, geoscientist assigns numerical values for the defined and structured events. First, by identifying the critical - lowest probability factors, then further refine that value toward the middle, higher values; and qualify it before determining final probability of the event.
5. Verifying: this step is for reviewing the quantitative assessments in preceding step. This assures the geoscientist presents judgments that reflect his pure beliefs accurately, and check the coherence of event structure.

This SRI method (Bratvold and Begg, 2010, p.176-181) of probability assessment is a systematic approach to comprehensive problems in geoscientist elicitation process. It informs possible bias that might occur in each sub-step. Thus, the process provides insights and transparency of geoscientist's assessment and estimate for decision maker; that improve decision quality.

5.3 General framework for probability verification (Weather forecast science)

Learning from the past to improve the future work is both a part of our daily life and exploration life. However, geoscientists assess their quality of uncertain evaluation about prospects; they often concentrated on technical problems and used simple statistic measures to verify it.

Murphy and Winkler (Murphy and Winkler, 1987) developed an extensively framework for verification of probability assessment in weather forecasting. That is, a joint distribution p(f,x) of forecast (f) and observation (x). In our language of exploration, we can address the forecast as the subjective probability assignment for the event of POS or value of the reservoir parameters; the observation is the outcome of a new field wildcat (NFW) or the post-value of reservoir parameters that the exploratory well penetrated.

Take the simplest verification case for probability of success that assesses for a NFW event. We can define

$$f = \begin{cases} 1, \text{ if the oil is assigned,} \\ 0, \text{ if the dry is assigned,} \end{cases}$$

And

$$x = \begin{cases} 1, \text{ if the oil is occurs,} \\ 0, \text{ if the dry is occurs} \end{cases}$$

We also can define a joint probability table for the event (**Figure 14**)

		Assigned Probability	
		Yes (1)	No (0)
Actual outcomes occur	Yes(1)	(1,1)	(1,0)
	No (0)	(0,1)	(0,0)

Figure 14 Probability table for 2-alternative event

With respect to estimating prospect reserves, that is a continuous distribution – represent in intervals of values. The joint probability p(f,x) also can depicted in terms of a contingency table as above.

Based on evaluation of p(f,x), we can know which probability assessment is "good" and which one is "bad". By looking at the Table, we can see the good assessments take two values of (1,1) and (0,0) – the probability assignment is perfectly correct. And the bad judgments take the other two values of (1,0) and (0,1).

For the intervals of values, the perfect judgments implies that all the pairs of assignment – outcome (f-x) are on the line f = x or on the principal diagonal of the contingency table. Alternatively, in a scatter plot as **Figure 15** the perfect probability prediction is diagonal line, if the points are under that line – it is overconfidence case. If the points locate above that line – it is under confidence case. The overconfidence and under confidence are both bad aspects of the judgments.

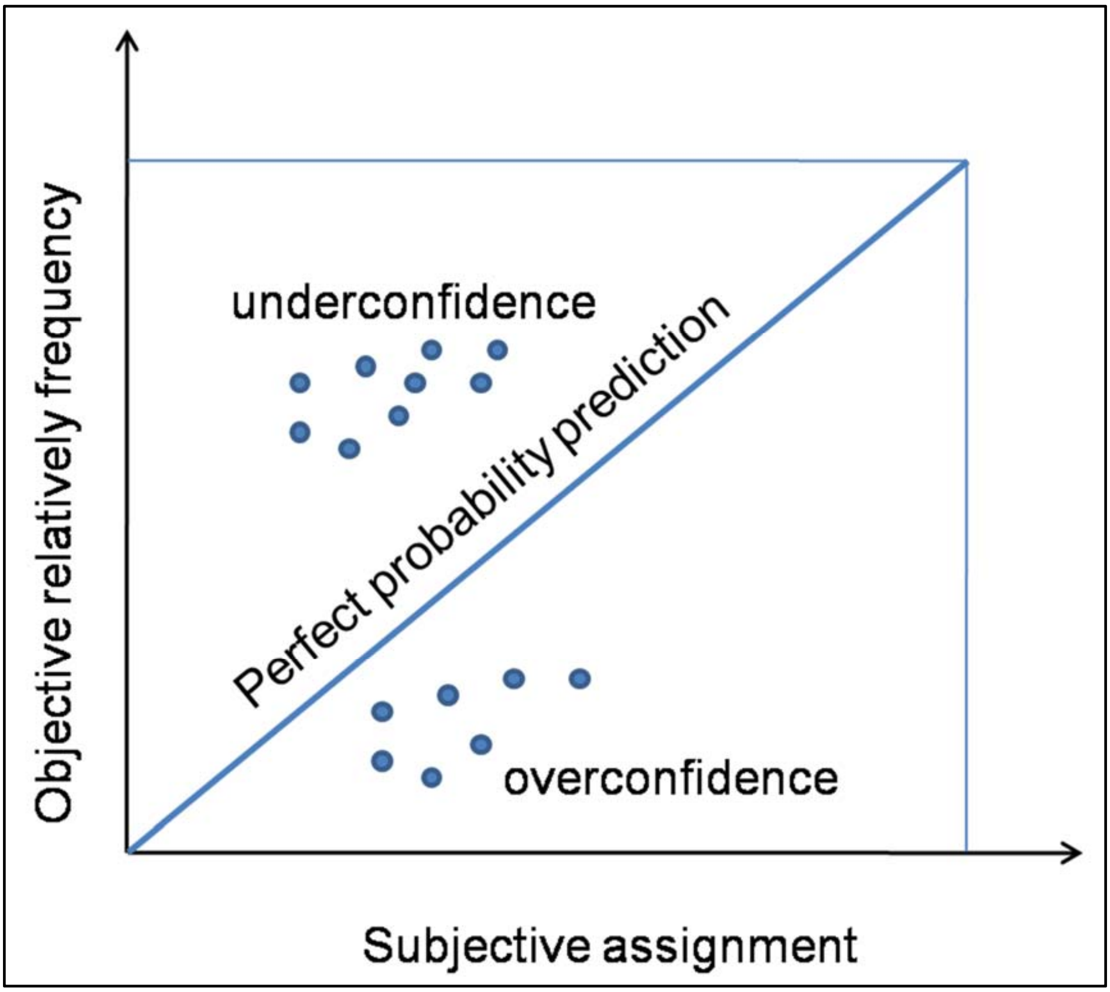

Figure 15 Estimates versus Actual outcomes

We need to factorize joint distributions into conditional distributions and marginal distributions. By this factorization, we can learn more insights about specific characteristics of probability assessment system, and the person who do that task – the geoscientist.

There are two ways of factorizations, the calibration-refinement and likelihood-base rate factorization.

5.3.1 Calibration-refinement factorization

$p(f,x) = p(x|f)*p(f)$ (3)

Where, $p(f,x)$ is joint distribution of forecasts/judgments and observation outcomes. $p(x|f)$ is conditional distribution of observations given forecasts and $p(f)$ is marginal distribution of forecasts.

The conditional distribution $p(x|f)$ – the possible outcomes occur given a particular assigned probability or prediction. This is the reliability or calibration of the assessment; we expect that this distribution is as large as possible. For example, p(oil| "oil") and p(dry| "oil") are the proportion of occasions with oil occurring among all of the occasions on which an assessment of oil was given. This can be criteria to select the expert's opinion for combination, which mentioned in chapter 4.

The marginal distribution $p(f)$ indicates how often different assessed values are used. The assessments are said refined or sharp if different values of (f) are used most of the time. Because that assessment system is able to distinguish oil contained prospect and others. If a geoscientist always assigns a value of probability assessment for different prospects, it means that he cannot differentiate which prospect can hold oil and which cannot. At the perfect sharpness, $p(f)$ is assigned zero and one.

Both distributions $p(x|f)$ and $p(f)$ are interested for probability assessment verification. We would to have a geoscientist who is both well calibrated and quite refined. The assessment is said "least useful" if $p(x|f) = p(x)$, it means, the forecast/assessment is not effect to the occurrence of the events, they are independence.

5.3.2 Likelihood-base rate factorization

The second way of factorization a joint distribution is:

$p(f,x) = p(f|x)*p(x)$ (4)

Where, p(f|x) is the distribution of probability prediction / assessments given the observation of the outcome happen; p(x) is the marginal distribution of the observations / actual outcomes. That is the proportions of different assessments are given before particular outcomes actually occurring. It provides information of discrimination among the actual outcomes and the assigned probability situation itself.

The p(f|x) is called the likelihood function – the assessment in concerning only particular outcome. For example, p("oil"|oil) is the occasion of probability assessment concerns the observation of oil presence. These likelihoods indicate how well the assessment / prediction f discriminates between prospects with x = 1 (oil) and prospects with x = 0 (dry).

The marginal distribution p(x) indicates how often different outcomes of x occur. For example, with POS, it indicates the relative frequency of oil and the relative frequency of dry prospect. The p(x) also referred to as the base rate or the historical discovery rate of a trend or sedimentary basin. However, in exploration context, the base rate is determined on the sample space of drilled prospects only, not entire prospects in the basin. Because companies will not drill small size prospects, or non-potential (dry) one that evaluated by geoscientists.

5.3.3 Relevant measures of verification

The common measure of accuracy of forecast – the mean square error (MSE) can be expressed by the joint distribution as:

$$MSE = E[(f-x)^2] = \sum_f \sum_x (f-x)^2 p(f,x). \qquad (5)$$

We can derive equation of MSE into several different ways to examine other attributes of the forecasts and observations. Additionally, other measures also can express by joint distribution and distribution elements to understand more about the verification quality, to improve assessment.

A quick conclusion, the joint distribution contains all of the relevant information that requires for verification purposes. By factorizing the joint distribution, the information of probability elicitation is more accessible. It is helpful to understand the strength and weakness in uncertainty assessment. Thus, it identify ways that make assessment might be improved.

Chapter 6 – Conclusion and Future work

In this research, the impact of the most prevalent biases on prospect evaluation and petroleum exploration decisions were practically addressed with the emphasis on modeling, simulating overconfidence bias and bias derived from trust heuristic. It is clear that geoscientists cannot deliver their promises to their managers if their geological uncertainty assessment – the prospect evaluation, is frequently imposed by cognitive biases (Rose, 2004).

The use of multiple experts can help to reduce overconfidence effect of using a single trusted expert, in sense of assigning input parameters. In addition, we have discussed approaches that employ to calibrate, verify the uncertainty assessments. Those are both practical used and new approaches: Rose's recommendation, SRI method and verification by weather forecast science.

From our findings and industry's observations, there is undoubtedly that oil companies realized the inevitable consequences of having biases in their works. They have started training their geotechnical staffs about the dangers of biases, how to detect the biases and calibrate their assessments. They applied systematically software that allows evaluating all new prospects. They formed a senior experts committee to review and approve prospect candidates before drilling.

However, companies are still doing poor E&P portfolios management, and bad choices. Such as, drill expensive dry holes, find marginal economically or non-commercial fields. Therefore, the intention of this thesis is to increase awareness and understanding the cognitive bias in geoscientists' work. Consequently, geoscientists may deliver what they promised to their companies, and companies may achieve what they planned to have.

There are a number of directions one could consider this research in the future. For example, one could model several biases simultaneously work in the same project to analyze which bias impact the most on prospect evaluation and corresponding exploration decisions. One could also attempt to model the expertise of experts to find the best way of combining experts' opinion to enhance the spreading expertise in company. Finally, one could investigate the use of probabilistic models of G&G cost, oil prices to have a completed probabilistic model.

References

Bratvold, R. B., and Begg, S. H. (2010). *Making Good Decisions*. Richardson, TX, USA: Society of Petroleum Engineers.

Brown, M. L., L. Fosvold, A. J. Garza, and D. M. Cook, (2000). *A look to the past to avoid old traps in the future*, *in* J. E. K. Kari Ofstad, and P. Alexander-Marrack, eds., Norwegian Petroleum Society Special Publications, v. Volume 9, Elsevier, p. 9-14.

Capen, E. C. (1976). *The Difficulty of Assessing Uncertainty*. J. Pet Tech 28 (8): 843– 850. SPE-5579-PA. DOI: 10.2118/5579-PA.

Capen, E. C. (1995). *A Problem With Experts*. Society of Petroleum Engineers. Paper presented at the SPE Hydrocarbon Economics and Evaluation Symposium, Dallas, Texas, USA.

Clemen, R. T. and Winkler, R. L. (2007). *Aggregating probability distributions.* In Advances in Decision Analysis: From Foundations to Applications, ed. W. Edwards, R. Miles, and D. von Winterfeldt. Cambridge, UK: Cambridge University Press.

Hammond, J. S., Keeney, R. L., & Raiffa, H. (2006). THE HIDDEN TRAPS IN DECISION MAKING. *Harvard Business Review, 84*(1), 118-126.

Lichtenstein, S., Fischhoff, B., and Phillips, L.D. (1982). *Calibration of probabilities: The state of the art to 1980. In Judgment under uncertainty*: *Heuristics and Biases,* ed. D. Kahneman, P. Slovic, and A. Tversky. Cambridge, UK: Cambridge University Press.

Mannes, A. E., Soll, J. B., & Larrick, R. P. (2014). *The wisdom of select crowds*. *Journal of Personality and Social Psychology, 107*(2), 276-299. doi: 10.1037/a0036677

Moore, D. A., & Healy, P. J. (2008). *The Trouble With Overconfidence*.

Psychological Review, 115(2), 502-517. doi: 10.1037/0033-295X.115.2.502

Murphy, A. H., and Winkler, R. L. (1987). *A General Framework for Forecast Verification*. *Monthly Weather Review, 115*(7), 1330-1338. doi: 10.1175/1520-0493(1987)115<1330:AGFFFV>2.0.CO;2

Rose, P. R., (1987). *Dealing with risk and uncertainty in exploration--how can we improve?* AAPG Bulletin, v. 71, n. 1, p. 1-16.

Rose, P. R., (2001). *Risk Analysis and Management of Petroleum Exploration Ventures* (Vol. 12): American Association of Petroleum Geologists.

Rose, P. R., (2004). *Delivering on our E&P Promises.* The Leading Edge 23 (2): 165-168.

Surowiecki, James. (2005). *The wisdom of crowds*. New York: Anchor Books.

Tversky, A., & Kahneman, D. (1974). *Judgment under Uncertainty: Heuristics and Biases*. *Science, 185*(4157), 1124-1131. doi: 10.2307/1738360

Vose, D. (2008). *Risk Analysis – A Quantitative Guide*, third edition. Chichester, UK: John Wiley & Sons.

Welsh, M. B., Begg, S. H., & Bratvold, R. B. (2007). *Modelling the Economic Impact of Common Biases on Oil and Gas Decisions*. Paper presented at the SPE Annual Technical Conference and Exhibition, Anaheim, California.

Winkler, R. L., and Murphy, A. H. (1968). *"Good" probability assessors.* Journal of Applied Meteorology, 7, 751-758.