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A framework for risking analysis with EM data

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Summary

Marine EM is routinely being used for hydrocarbon exploration about a decade but yet to find its way into the mainstream risking workflow of most exploration companies. We have developed a framework for incorporating EM data into a standard risking scheme and tested it for 12 prospects of Reliance blocks over Krishna- Godavari basin. The scheme shows consistent and fairly uniform results for the prospects.

Introduction

Using geophysical data to assess and compare geological risk of prospects in a portfolio is a central task in hydrocarbon exploration. Although there is no universal standard for this risking process, generally accepted frameworks do exist, for example (Otis, 1997). These frameworks can in principle be used with virtually any type of geophysical data. However, exploration companies have accompanying workflows and procedures which are often geared specifically towards traditional data types such as seismic. In particular, marine electromagnetic (EM) data cannot yet be said to have found its way into the mainstream risking workflow of most exploration companies – even among those that over the years have spent considerable resources on acquiring and processing EM data. Using the acquired EM data actively in risking and decision making is essential in order to obtain full value of information. Failure to do so has in the past all too often led to EM data being used only for internal evaluation purposes or simply shelved.

In this paper we propose an extension to a general risking framework, which allows for the inclusion of results from EM surveys. This framework is rigorous and consistent enough to capture the most important risking information which can be extracted from an EM survey, yet sufficiently flexible to be applied to a wide range of geological scenarios and to be tuned to suit the varying needs and preferences of different users. An example is given where the proposed framework is applied to a collection of EM datasets from the Krishna-Godavari basin offshore India.

Options for updating the probability of geologic success

Geological risk associated with a prospect is commonly quantified as a geological chance of success P_g. This probability is broken down into a set of risk factors, pertaining to different geological features that must be present in order for an accumulation of hydrocarbons to exist. The exact number and names of these factors may vary slightly within the industry, but for this study we adopt the definition of P_g introduced by (Otis, 1997):

$$P_g = P_{source} \times P_{reservoir} \times P_{trap} \times P_{dynamics}$$

The expression for P_g states that a petroleum accumulation will occur if and only if all the four play elements source, reservoir, trap and dynamics are present and favorable. It also implicitly states and requires that the play elements' existences are mutually independent.

When we now want to introduce EM data into this or a similar framework, we face three main options:

1. Consult the EM data where relevant in the assessment of the individual geological sub- factors contained in the original framework.

2. Modify or extend the original framework with some EM-specific factors.

3. Construct a separate EM risking framework.

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All of these options have their own advantages and disadvantages. Keeping in mind the undeniable complexity of the processes, we have used the second scheme in this paper as it has enough liberty in tailoring a risking framework and also pay due attention to the existing framework.

Defining and evaluating EM risk factors

We introduce two new EM-based risking factors to compliment P_g: A probability factor P_{EM}, for the probability of the presence of a subsurface resistivity anomaly caused by hydrocarbons; and a weight factor W, to represent the level of confidence in EM and decide how much a particular EM dataset can shift the original P_g value. The resulting *chance of success* (COS) figure will have a somewhat different interpretation than P_g since, while P_g says nothing about the volume of hydrocarbons in place, the EM method requires a certain quantity of high resistive matter to be present in order to have sensitivity.
An intuitive way of combining the EM risk factors with P_g is through a weighted average:

$$COS = (1 - W) \times P_g + W \times P_{EM}$$

While weighted averaging is hardly a formally correct method for updating statistical probability, it does have the benefit of being simple, transparent and easy to calibrate.

When using EM data in risking we are interested in answering two fundamental questions:

- Is there a resistivity anomaly in the target zone?

- Is this anomaly caused by an accumulation of hydrocarbons?

The answer to the first of these two questions is found primarily in the EM data itself, while the second is a matter of geological interpretation which requires integration of EM data with other available geophysical data. We want the P_{EM} factor to represent a graded response to these two questions on a scale from 0 to 100 (percent), given the data at hand. The weight W should represent the confidence we have in the data material.

In order to perform these assessments on individual prospects we have devised a questionnaire which asks the user to rate various characteristics of the EM data, results from modeling and inversion studies, and interpretation aspects on a scale from "unfavorable" to "favorable". This is conceptually similar to the risking scheme proposed by (Otis, 1997) for traditional risking, and also the AVO risk analysis workflow proposed by (Roden, et al., 2005). As for P_g, the PEM factor is composed by 4 factors:

$$P_{EM} = P_{ANOMALY} \times P_{RESISTOR} \times P_{BACKGROUND} \times P_{HYDROCARBON}$$

Similarly, the weight W is composed of a data quality factor and a processing factor.

Table 1 shows the results for one selected prospect. The total PEM and W are found my multiplying their factors, an approach which mimics the mechanism in the framework by (Otis, 1997), admittedly without being overly concerned with the issue of the factors' statistical independence. All that remains at this stage is to combine the EM-driven factors with the original P_g. Assuming an initial P_g of 20%, we arrive at a weighted average COS of 33%. In order to arrive at this number it is also necessary to apply a data independent weight. As it is unrealistic to assume the EM can have larger influence than other geologic and geophysical factors, the data independent weight will reflect each individual company's confidence in EM as an exploration tool.

Table 1: An example showing how to calculate P_{EM} and W in the proposed risking scheme.

Category	*Unfavourable*	*Neutral*	*Favourable*	*Score*
$P_{Anomaly}$	0	0	3	100%
$P_{Resistor}$	0	1	2	83%
$P_{Background}$	0	2	2	75%
$P_{Hydrocarbon}$	0	1	2	83%
Total P_{EM}:	**0**	**4**	**9**	**52%**
EM data weight	0	1	3	88%
Processing weight	0	2	2	75%
Total weight:	**0**	**3**	**5**	**81%**

Database trends

We have applied the framework described above to five EM exploration surveys in the Krishna-Godavari basin. Most of these cover more than one prospect, and we have chosen altogether twelve prospects for this analysis. Figure 1 shows a map of the location of the selected surveys and pre-EM prospect outlines.

The results of applying the EM risking scheme to the twelve prospects are summarized in Figure 2. In the chart on the left we see the EM risking factors P_{EM} and W. The weights are fairly uniform, ranging between 50% and 81%, with one exception. This reflects the high similarity between the studied surveys; they are all from the same geographical area, acquired within the same time period and with roughly the same survey setup and data processing work.

The right hand chart in Figure 2 displays the updated chance of success for the twelve prospects. Results are shown both for the weighted average method described above, and two other updating mechanisms which will be discussed in the next section. The initial P_g estimates are unknown, so we have assumed a uniform value of P_g = 20% for all the prospects. Comparing the methods, we see that the weighted average method tends to update the chance of success more than the two others. The difference is most pronounced for those surveys with high values of P_{EM}.

Calibrating and tuning the framework

We do not expect all readers (or any) to fully agree with the details of the EM risking framework presented above. Naturally our proposed scheme is but one of infinitely many possible variations and each EM user must decide on their own preferred questionnaire and mechanism for combining the EM risk factors with the initial P_g. Different exploration companies have different ways of assessing and risking prospects, and the work with EM should reflect this. It is however important to apply the same scheme consistently to all prospects which are to be internally compared, for example in a ranking process. When designing and calibrating the EM risking framework it may be helpful to consider the following key questions:

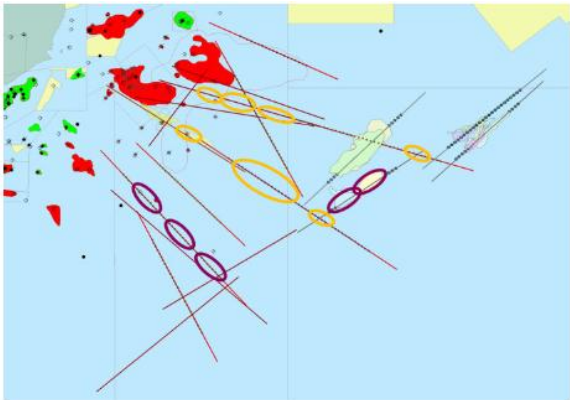

Figure 1: Map of the surveys and prospects which were selected for analysis.

- How much is the company willing to let EM influence the COS? This question deals with the general confidence in EM, and the significance compared to seismic information.
- What magnitude of change in P_g is required in order to influence decisions? If the risking framework denies EM data a real potential to change drilling decisions, the value of information (VOI) will always be zero.

The answers to these questions will give guidelines to the acceptable value ranges for P_{EM} and W, and the scheme can be adjusted accordingly.

One key to calibrating the framework is in the coupling of the EM risking factors with P_g into a total COS. Above we used weighted averaging, but a trained statistician will likely argue that Bayes' rule is a more correct approach. Bayes' rule is a general statistical mechanism for calculating the updated probability of an event given new, uncertain information (Wikipedia, 2011), which in our case takes on the form:

$$P(H|A) = \frac{P_g P(A|H)}{P_g P(A|H) + (1-P_g) P(A|H')} \quad \text{or}$$

$$P(H|A') = \frac{P_g P(A'|H)}{P_g P(A'|H) + (1-P_g) P(A'|H')}$$

for positive and negative EM results, respectively. Here *A* is the event of a positive EM result, *H* is the event of drilling success, and *A*' and *H*' are their complementary events. The four factors P(A|H), P(A'|H) etc are expressions of the accuracy of EM at predicting the drilling outcome. In (Buland, 2010) they are collectively termed EM prediction strength. We will, like Buland, make the simplifying assumption that P(A|H) = P(A'|H'), meaning that EM is equally good at predicting discoveries and dry wells. As our estimate of the prediction strength we will use the weight factor W, scaled to range from 0.5 to 1, since in Bayes' rule P(A|H) = 50% is a coin-flip which yields no probability update. The final updated COS is

$$COS = P(H|A) \cdot P(A) + P(H|A') \cdot P(A')$$

$$= \frac{P_g W}{P_g W + (1 - P_g)(1 - W)} P_{EM} + \frac{P_g(1 - W)}{P_g(1 - W) + (1 - P_g)W}(1 - P_{EM})$$

Another approach is to construct a formula that behaves according to expectations, i.e. such that the resulting values of COS are consistent with conventional P_g values, while the EM-induced changes are realistic. We have found that the following formula yields good results in the cases we have analyzed:

$$COS = P_g[1 + (P_{EM} - P_g)]$$

As we can see from Figure 2, this formula tends to be more conservative than the other two we have tried. A case to note from Figure 2 is prospect number 12, where the Bayesian method pulls the chance of success down while the two others do the opposite. With P_{EM} = 23%, the weighted average and empirical methods tell us that the chance of success has increased, since $P_{EM} > P_g$. According to Bayes' theorem, however, this EM result does not strengthen the case for a discovery, since P_{EM} is less than 50%. This observation has the important implication that the "neutral" value of P_{EM} is different for the methods; for the Bayesian method it is 50% while for the other two it is the original value of P_g.

Conclusions

Our framework for incorporating EM data into risking scheme shows consistent and fairly uniform result over test prospects. If EM data shall have a considerable Value of Information (VOI) it must be allowed to influence drilling decisions. The best way of ensuring this, is to have a method for involving EM in the risking process. Fine tuning of the risking frame work may require deeper geological knowledge and correct exploration statistics for a particular basin.

References

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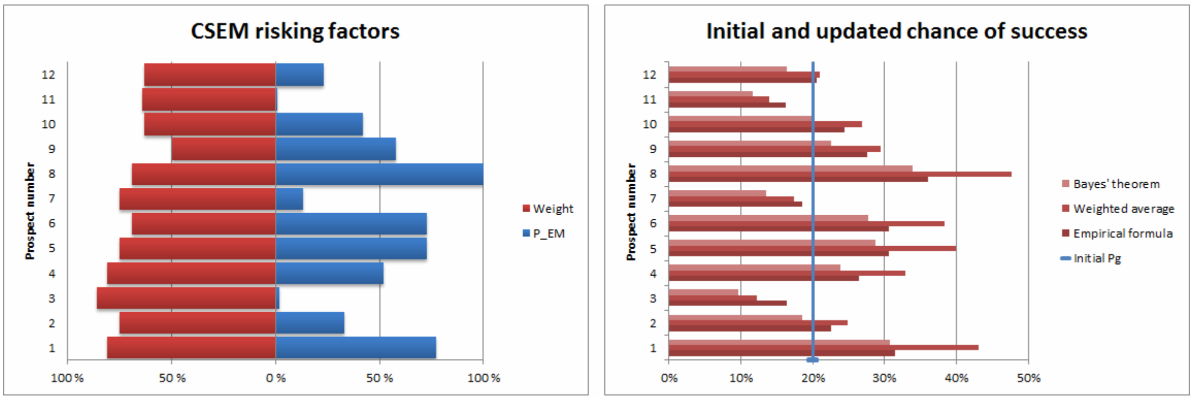

Figure 2: EM risking results for the twelve evaluated prospects. Left: EM risking factors. Right: Updated chance of success with the three different updating approaches described in the text.