

**AAPG HEDBERG CONFERENCE**  
**“APPLICATIONS OF RESERVOIR FLUID GEOCHEMISTRY”**  
**JUNE 8-11, 2010 – VAIL, COLORADO**

**Geochemical Allocation of Commingled Oil Production and/or Commingled Gas  
Production from 2-6 Pay Zones**

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We have made significant improvements to the previously published methods for geochemical allocation of commingled oil production and/or commingled gas production.

Previous methods for using oil composition differences to allocate commingled production from a single well have been detailed in Kaufman et al. (1987 and 1990). Similar methods for allocating the contribution of multiple fields to commingled pipeline production streams are discussed by Hwang et al. (2000). The methods described in those publications relied on using GC peak ratios to quantify the contribution of multiple zones to a commingled production stream. In brief, if two zones were being commingled (“Zone A” and “Zone B”), then, in those publications, the respective contributions of Zones A and B to a commingled sample were determined by identifying chemical differences between “end-member” oils (with the end members being a pure sample of oil from Zone A and a pure sample of oil from Zone B). Geochemical parameters (GC peak ratios) reflecting these compositional differences were measured in the end member oils, in various artificial mixtures of the end member oils, and in the commingled oil. The data were then used to mathematically express the composition of the commingled oil in terms of contributions from the respective end member oils. Using this simple mixing model, a single geochemical difference between oils from two sands is sufficient to allocate commingled production from those two units. By using data for several peak ratios, independent solutions to the problem could be derived, allowing the accuracy of the allocation to be assessed.

This older approach for geochemical allocation had two drawbacks: (1) it required analysis of artificial mixtures of the end member oils, and (2) it could not readily be applied to mixtures of more than 3 end member oils. It was necessary to make artificial mixtures of the end member oils because GC peak ratios do not necessarily mix linearly: ratios only mix linearly when the same number is present in the denominator of the two ratios being mixed ( i.e.,  $7/2$  mixes linearly with  $9/2$ , but does not mix linearly with  $9/3$ ). Therefore, artificial mixes of end member oils had to be prepared to determine the shape of the calibration curve that defines how a given GC ratio changes as one moves from 100% Oil A to 100% Oil B. Furthermore, as mentioned above, allocation was limited to 2 or 3 zones. This limitation arose because, for a given GC ratio, two end members when mixed form a mixing curve, and 3 end members when mixed form a mixing surface, but, when more than 3 end members are mixed, there is no simple graphical representation of the mixing from which one could derive a solution.

McCaffrey et al. (1996) proposed an alternate approach that was based on GC peak heights and not GC peak ratios. This approach had the advantages of NOT requiring analysis of artificial mixtures of end member oils (since peak heights always mix linearly) and also being applicable to any number of mixed zones.

The method described here is based on the McCaffrey et al. (1996) approach. In brief, the concept is as follows:

If there are no systematic sources of error, then the relationship between the GC peak-height “Y” (measured in the GC trace of a commingled oil) and the GC peak heights “X” of the corresponding peaks in the “m” end-members oils being commingled is given by a linear relationship of the form:

$$Y = \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_m X_m.$$

Production allocation is the process of determining the values of  $\beta$ .

However, in reality, there are multiple sources of error. For example, there is (1) analytical error in measuring the values of each GC peak, (2) error associated with potential contamination of GC peaks, and (3) error associated with the non-ideality of the samples chosen as end members (for example, when end member oils are taken not from the same well as the commingled oil, but rather from nearby single-zone producing wells that may not be laterally continuous with the commingled well). As a result of the various sources of error, certain GC peaks will do a better job than other peaks at allocating the contributions of each zone to a commingled oil. We cannot know in advance which GC peaks will do the best job, and, in an oil allocation project, data for many hundreds of different GC peaks are available.

This problem, therefore, becomes a problem of linear regression. Specifically, given a set of samples containing a value for each independent variable and the corresponding value of the dependent variable, we seek to compute the  $\beta$  values in a relationship of the form:

$$Y = \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_m X_m + \text{eps}$$

Where, “eps” represents the error that is not captured by the linear relationship.

Linear regression can be used to converge upon a set of  $\beta$  values that minimizes the sum of the square of the errors. For example, as noted by McCaffrey et al. (1996):

$$\beta = (X'X)^{-1} X'Y$$

is a simple way to derive an estimate of the  $\beta$  vector. In numerous un-published studies conducted between 2000 and 2009, we have found that significantly better estimates of the  $\beta$  vector can be derived by (1) applying certain scaling techniques to X and Y, (2) utilizing information revealed by the structure of the variance within the dataset, and (3) eliminating from consideration GC peaks with certain specific characteristics.

Given our best calculated estimate for the  $\beta$  vector, we are then able to compute the error in each sample point, square that error, and sum it to give S. This value is used to compute the variance of eps as:  $S/(n-m)$ , where n is the number of peaks and m is the number of end-members. This gives sigma, the standard deviation of eps.

$\beta$  is not a single number, it is a vector; therefore, its distribution is a joint distribution. As a result, we can again use linear regression to compute the variances in the elements of the  $\beta$  vector from variance of eps. This gives us the standard error in  $\beta_j$ . Finally, we can use that value to compute the confidence interval around  $\beta_j$ .

Over a four year period, we conducted eight separate blind tests of this approach in which various outside laboratories prepared multiple mixtures of 2-6 end member oils, and did not reveal to us the contribution of each end member to each mixture. For each study, we analyzed the mixed oils and the end member oils by GC, and from those data (and the linear algebra approach described above) we were able to derive very accurate allocation results. The 8 blind tests collectively included >30 commingled oils, each prepared by mixing 2-6 end member oils. In almost all cases, the allocation results that we calculated were found to differ from the “actual” results by <5%, and commonly by <2%.

We conducted field tests of this geochemical allocation approach in two fields in which geochemical allocation results were calculated for numerous samples of “real” commingled oils, and then those allocation results were compared with six separate Production Logging Tool (PLT) results for the same wells. In both fields, the close correspondence between the geochemically derived results and the PLT-derived results caused the field operator to discontinue use of PLT monitoring of the fields, and instead proceed solely with geochemical monitoring.

The approach described above works because all of the equations that describe mixing are of the form:

$$Conc(c) = \sum_{i=1}^n Conc(c, i) \times frac(i)$$

In other words, they are linear. This approach is, of course, not applicable if one attempts to use isotope data (instead of GC peak heights) to discriminate between end members (such as one may be tempted to do in a gas allocation project). This is because the equations that describe the mixing of isotopic measures are more complex. Specifically, they are of the form:

$$Iso(c, e) = \frac{\sum_{i=1}^n Conc(c, i) \times Iso(c, e, i) \times frac(i)}{\sum_{i=1}^n Conc(c, i) \times frac(i)}$$

However, this equation can be rearranged to:

$$\sum_{i=1}^n Conc(c, i) \times frac(i) \times Iso(c, e) = \sum_{i=1}^n Conc(c, i) \times Iso(c, e, i) \times frac(i)$$

This equation can then be further rearranged to:

$$\sum_{i=1}^n Conc(c, i) \times (Iso(c, e) - Iso(c, e, i)) \times frac(i) = 0$$

This is a linear equation, which can then be treated just as we treated the equations for mixing of GC peak heights. However, unlike the equations that represent the mixing of concentrations, these concentration-weighted isotope equations represent lines that pass through the origin. The following illustration helps to clarify this concept. Consider a commingled gas that is a mixture of two end-members:

End Member	%		‰	
	C <sub>1</sub>	C <sub>2</sub>	δ <sup>13</sup> C <sub>1</sub>	δ <sup>13</sup> C <sub>2</sub>
1	90.00	10.00	-70.00	-50.00
2	80.00	20.00	-60.00	-40.00
Commingled Gas	85.00	15.00	-66.00	-43.00

In the table above, the concentration of the components C<sub>1</sub> and C<sub>2</sub> in the commingled gas are correct (as per the linear mixing rule), but, but for the sake of illustration, the carbon isotopic values of the commingled gas have been intentionally altered from the values one would obtain by using the formula for mixing of isotopic values (-65.29, -43.33); therefore, we have intentionally introduced “error” into the isotope data for the commingled gas.

There are three types of linear equations that describe the data in this table: (1) equations for mixing of component concentrations, (2) equations for mixing of isotopic values of components, and (3) an equation to ensure that the fractions sum to 1.

I. Methane Concentration:  $85 = 90 \times \text{frac}(1) + 80 \times \text{frac}(2)$

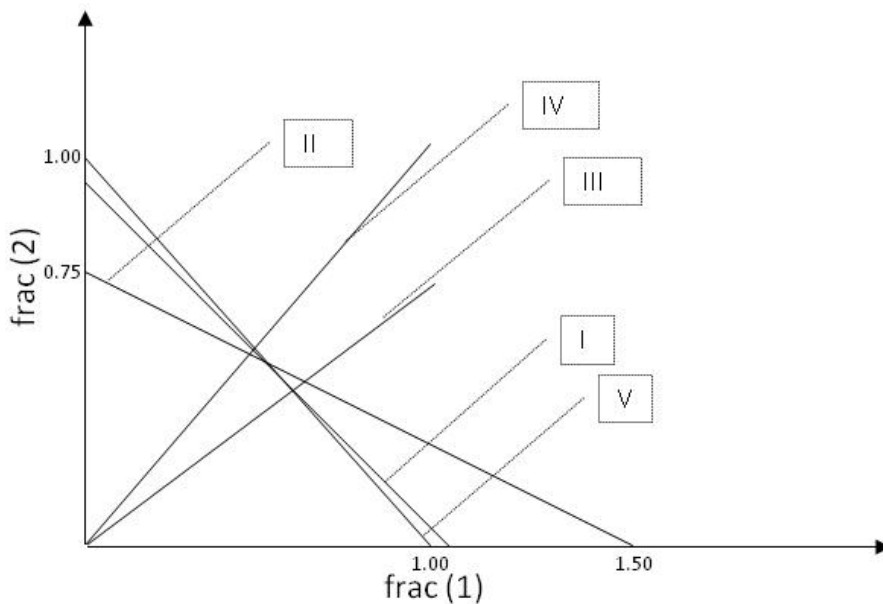
II. Ethane Concentration:  $15 = 10 \times \text{frac}(1) + 20 \times \text{frac}(2)$

III. Methane Carbon Isotopes:  $90 \times ((-66) - (-70)) \times \text{frac}(1) + 80 \times ((-66) - (-60)) \times \text{frac}(2) = 0$

IV. Ethane Carbon Isotopes:  $10 \times ((-43) - (-50)) \times \text{frac}(1) + 20 \times ((-43) - (-40)) \times \text{frac}(2) = 0$

Finally, we have the equation that enforces the requirement that the fractions add up to 100%:

V.  $\text{frac}(1) + \text{frac}(2) = 1$ . Graphically, these 5 equations in 2 variables can be represented as follows:



The lines representing the 5 equations do not intersect at a unique point because we introduced “error” into the isotope data for the commingled gas. Linear algebra can be used to derive the best compromise solution. In addition, this graph demonstrates a difference between problems that do and do not use isotope data: Where only concentration data are used, every equation is a line with a negative slope with positive intercepts on both axes. In the general case, every equation is a hyperplane in n-dimensions (where n is the number of end-members) with positive intercepts on each dimension. In contrast, the equations that govern mixing of isotopic values are lines that pass through the origin. In the general case, equations that govern mixing of isotopic values are hyperplanes in n-dimensions (where n is the number of end-members) that pass through the origin.

## References

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