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Creating More Representative Type Wells

Randy Freeborn, SPE, SPEE and Boyd Russell, SPE, SPEE, Energy Navigator Inc.

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Abstract

This paper presents original research on how to improve the predictive ability of type wells used in evaluating unconventional resource drilling programs by extending traditional Monte Carlo calculations. The paper addresses three critical questions engineers must answer before constructing a type well: which well to use in the construction, the relative importance (weighting) appropriate for each well, and how to adapt the results to reflect certainty (e.g. P10, P50 or P90).

The proposed method involves determining the aggregated distribution of estimated ultimate recovery (EUR) for the specified number of wells by running a statistically significant number of Monte Carlo trials. From this distribution, one can determine mean EURs for the desired type well certainties, such as P50 or P90. Additional Monte Carlo trials yielding the desired mean EUR will help determine which wells to average. Monte Carlo sampling results in several hundred trials that match the desired EURs. The relative frequency of well selection from these trials defines the weighting factor and thus the relative importance of each well. Type wells result from a weighted averaging of history and production from the selected wells.

Engineers can use this new methodology to prepare production profile forecasts for the evaluation of multi-well unconventional resource drilling programs. They can also gain an understanding of the impact aggregation will have on their evaluation work.

Our research concludes that current type well construction practices may not be appropriate for evaluating future drilling because the production profiles for the wells used to build the type well may differ from the production profiles of the planned wells. This paper presents a new method to obtain more representative type wells. The method permits defining any uncertain parameter (e.g. EUR, net present value or payout time) and then building a type well for various measures of probability of attaining that parameter.

This paper presents new concepts that contribute to the technical knowledge base.

- We present a method to calculate probabilistic type wells based on the likelihood of drilling wells that make up the distribution of EUR (or other parameters). The method

combines the concepts of aggregation and Monte Carlo simulation to calculate weighting factors for use when averaging rate-time profiles.

- We introduce the paradigm that one can build probabilistic type wells from distributions of parameters other than EUR. EUR is only suitable for determining reserves. When conducting an evaluation, one may want a more relevant type well; for instance, one that examines the ability to self-finance by representing the probability of recovering a percentage of capital expenditure in the first year.
- We present a method to scale rate-time profiles from representative wells to the fracture geometry and reservoir quality of future drilling prospects. These scaled wells are for use in building type wells. The scaling algorithms also prove useful in estimating fracture geometry and reservoir quality where it is unknown.

Background

The literature offers some confusion between the terms “type well” and “type curve”. In this paper, we define type well as a rate-time production profile, most commonly created by averaging rate-time production profiles from analogous wells. One may also create type wells using reservoir simulation, rate-time analysis and other analytical methods. The distinguishing feature is that we use *type wells* to represent the average performance of existing wells or wells that are about to be drilled. In contrast, we consider a *type curve* to be a dimensionless analytical or numerical solution presented graphically and used to predict well performance using an overlay methodology.

Vanorsdale (1987) reported building a typical decline curve well that included normalizing data to a common standard measurement. He used elapsed time to have a common first production date and he used dimensionless rate defined as the ratio of each well’s rate to its peak rate. Vanorsdale’s wells had 40 to 50 years of production history, so he did not face the issue of declining well count as more recently drilled wells ran out of production to include in averages.

Sutton, Cox and Barree (2010) studied the Barnett Shale using methods reported by Vanorsdale; namely time shifting production to a common starting time and averaging the rates – a method they term a common industry practice. Sutton et al. suggested excluding data near the end of the time cycle because the decrease in well count can influence the averages.

We have not found a reference to creating type wells that represent a specified probability or certainty level; however, AJM Petroleum Consultants (AJM) in Calgary may have devised the first method to create probability-based type wells. AJM used a proprietary time slice method that is in common use today and described by Freeborn et al (2012). Haskett (2005) also described the need to have multiple rate-time profiles to represent different levels of certainty.

Time slice (author’s terminology) is a method to create probability-based type wells and is the method used in most commercial software. For each production month, one sorts the individual well rates. From this ranked listing of rates, one selects the rate corresponding to the desired probability as the rate for that month. Common practice is to process historical production data until too few wells have data to process (a fixed percentage of the total number of wells in the range of 75%). Then, one completes the rate-time production profile using decline analysis.

Freeborn et al (2012) provided a critical review of current type well methods. Like Sutton et al (2010), they confirmed that declining well count creates inaccuracies. Case studies demonstrated the improved accuracy from their recommendation to build type wells using a combination of history and prediction.

They found inaccurate results from the time slice method but could not articulate the reason. As an alternative, they recommended defining a target EUR from aggregation tables (e.g. SPEE 2010) and constructing a mean type well from a subset of the source wells that represent that target EUR.

Russell et al (2013) reported that inaccurate type wells result from the time slice method when source well rate-time profiles are not parallel, but cross one another. They also recommended a method called Analog Forecasting that uses type wells to extend the production "history" of wells with short production lives.

The authors acknowledge Russell Hall's course on Monograph 3 (Hall 2013) as providing the seed for this paper and the Aggregation Type Well construction method that we propose. He showed time-lapse Monte Carlo calculations for the aggregation of EURs from a multi-well drilling program, and from those time lapses, we grasped the concept that there must be information available from Monte Carlo simulation to apply to type well construction.

Aggregation Principles

We provide this discussion to ensure a basic understanding of aggregation principles, because aggregation will be the first step taken toward constructing an aggregation-based type well.

We will show that the probability distribution depends on the number of samples taken from that distribution. For example, the average EUR expected from drilling three wells will differ from the average EUR from drilling ten wells. To create an aggregation type well, we will need to specify the number of wells we will drill and the certainty level desired for the type well.

Distribution characteristics	
μ, logarithmic mean	2.960
σ, logarithmic standard deviation	0.330
R^2	0.990
Sample mean	1136
Swanson's mean	1194
P10/P90 ratio	7.02

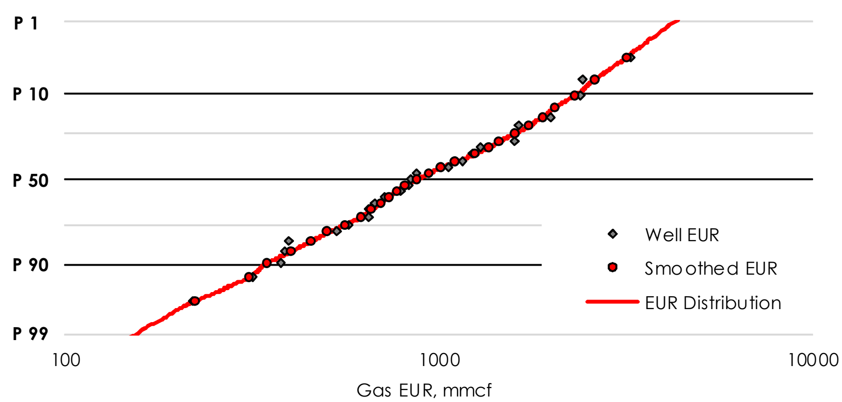

Figure 1
Wild River EUR Distributions

The probability distribution plot in Figure 1 displays the estimated ultimate recovery from twenty-seven vertical gas wells (grey diamonds). These wells are conventional, vertical, fracture stimulated wells located in the Wild River field in Alberta, Canada. The wells are in close proximity to one another, and have similar pay quality and completions.

The well EURs result from forecasting three years of data using a modified hyperbolic equation with a five percent nominal terminal decline. EURs calculated in this manner have random error associated with the decline analysis and a potential bias associated with the imposed terminal decline. By forecasting individual wells, the random errors will tend to cancel, resulting in a better overall EUR distribution. EUR's could also be determined from rate time analysis (RTA) or reservoir simulation. The

EURs and distributions shown in Figures 1 and 2 serve as an example to demonstrate common aggregation principles and other engineering practices.

You must follow proper practice for selecting representative wells. This means selecting wells that represent the reservoir quality and completion of the wells you plan to drill. Further, not all operators are the same: do not choose wells from a first decile operator if you are in the third quartile. If your sample size is too small, consider adding wells that will become representative with appropriate scaling of the rate-time profile.

A probability distribution, like that in Figure 1, represents the EUR from a number of wells, taken one at a time. In an aggregated distribution each data point would represent more than one well and is the mean EUR from those wells. Therefore, a probability distribution represents the EUR from a number of individual wells and an aggregated distribution represents the mean EUR from a number of wells, normally the size of the drilling program being evaluated using the aggregated distribution. This subject continues in a few paragraphs.

As expected, the EUR from this set of wells is log normally distributed (as evidenced by the linear shape of the data plotted on a logarithmic scale), but there is some minor deviation from linearity at extreme probabilities. With this many data points and the observed deviation from linearity, we choose to smooth the observed actual distribution instead of using a logarithmic regression fit. The choice to fit the data with a lognormal distribution is at the discretion of the evaluator, but we do recommend a lognormal fit when the sample size is small.

To smooth, we fit seven consecutive points to a log normal distribution, using the centre-calculated point as the smoothed value. At the ends, where there are not seven points for smoothing, the smoothing reduces to five-point and then three-point. We also use the three-point fit to calculate the outlying smoothed data values.

To extrapolate beyond the data range, we fit the steeper slope that often appears at probability extremes. In this example, the extrapolation fit used four data points for high probabilities and five data points for low probabilities.

In this paper, we use the term aggregation to mean the construction of an EUR (or other parameter) probability distribution that would represent the number of wells that the evaluator plans to drill based on this distribution. To simulate the probable outcomes of a planned drilling program, we use Monte Carlo techniques. For a specified number wells, we select a random probability to represent each well and convert the probability to EUR from the single well distribution like that shown in Figure 1.

Wikipedia (2015) provides a brief understanding of the nature and use of Monte Carlo techniques:

- "Monte Carlo methods (or Monte Carlo experiments) are a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results."
- "Monte Carlo methods are … used in … generating draws from a probability distribution."
- "… examples include modeling phenomena with significant uncertainty in inputs such as the calculation of risk in business …"

In Figure 2, we show an aggregated distribution as a blue line. We determined the distribution by running twenty-five thousand Monte Carlo trials.

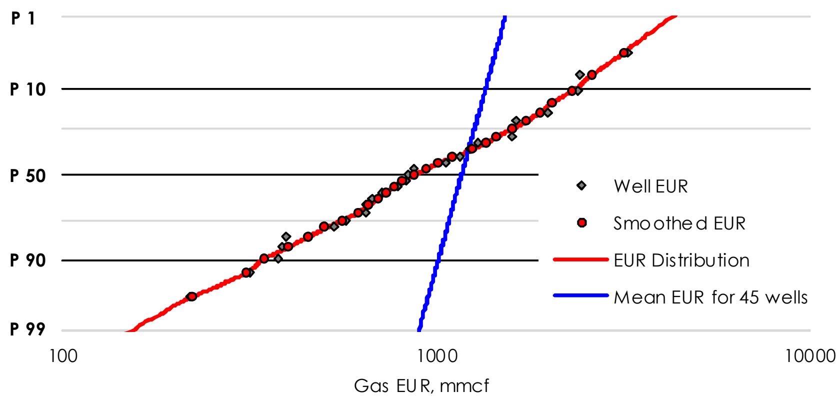

Figure 2
Wild River Mean EUR Distribution for 45 Wells

For each trial, we randomly selected forty-five probabilities, one for each of the wells we plan to drill, and converted them to EURs using the smoothed probability distribution of Figure 1, restated in Figure 2. The average of forty-five EURs is the mean EUR that is the single point representation for the one Monte Carlo trial. The referenced blue line is the distribution from all of the Monte Carlo trials.

The Central Limit Theorem suggests that the average of the samples from any distribution, including lognormal, tends to become normal when the sample size is large. From this theorem, one might expect a normal distribution for the aggregated distribution seen in Figure 2, but it is lognormal. To confirm that this is not a programming calculation error, we brute force calculated aggregated distributions for 45 and 1000 wells in a spreadsheet using 10,000 trials. We found a lognormal distribution for 45 wells and a normal distribution for 1000 wells. From this test, using the distribution of Figure 1, we conclude that a sample size of forty-five wells is too small to observe normality.

We choose to select probabilities in the range 0.1 to 99.9 percent. This is equivalent to a sample distribution of one thousand wells. This choice of probability range is discretionary, but should be balanced and narrow enough that selected EURs are not unbelievably large or small. On the other hand, the probability range should imply a well count that is large enough for proper sampling of the number of wells selected in the aggregation. For example, we believe that sampling P1 to P99 (one hundred wells) is too small for a drilling program larger than fifty wells because of the high probability of sampling outside that narrow range.

Rose and Associates, an industry leader in risk analysis, recommends the use of a technique called “spiking” to restrict the random sampling to a range of P1 to P99. With this procedure, one selects unrestricted random probabilities, but truncates the value when the selected probability is outside the acceptable range. This results in a characteristic spike at the endpoints, P1 and P99, for Rose and Associates’ recommended range. We believe this practice results in a conservative distribution because it limits the possibility for upside and downside EUR in large drilling programs.

The aggregated distribution, shown on Figure 2, has a steeper slope (and greater certainty) than the original smooth distribution. With increasing aggregated well count, the P90 EUR will increase and the P10 EUR will decrease. Eventually the aggregated slope will become vertical at the mean EUR. To demonstrate, we have created the trumpet plot of Figure 3 to show the aggregated distribution for a wide range of well counts.

We explain this increasing certainty by example. As we drill or sample more wells, the likelihood that all of those wells have the lowest reported EUR (220 mmcf) becomes very small. Thus, for the lowest reported probability, the expected EUR must increase as the well count increases. Similarly, the likelihood that all of the sampled wells have the highest reported EUR (6294 mmcf) is also very small. Thus, for the greatest reported probability, the expected EUR must decrease as the well count increases.

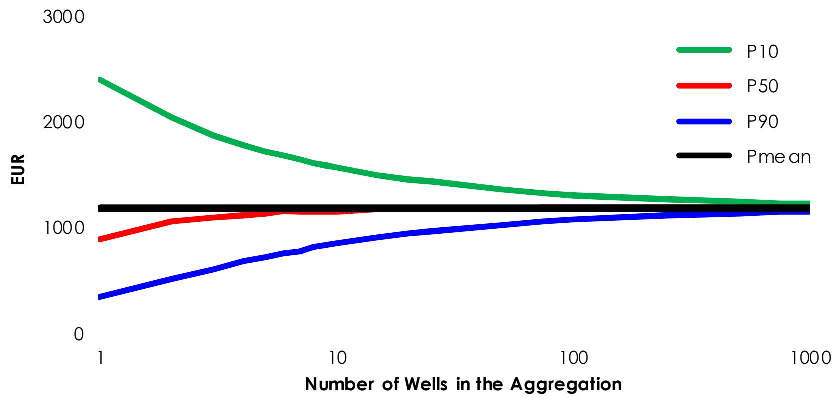

Figure 3
Wild River Aggregation Trumpet Plot

We observe that drilling multiple wells will increase both the EUR certainty, and the proved and probable reserves values. A company that administers its reserves without aggregation understates its reserves. It would benefit from changing its current practices.

A Recipe for Aggregation Type Wells

With aggregation type wells, we need to establish an appropriate weighting factor for each well in the probability distribution. The weighting factor should represent the chance of drilling each well in a program of specified well count and certainty expectation.

This section of the paper will state and explain four steps required to construct an aggregation type well that meets our objective. In some aspects, it is like following the recipe in a cookbook. As a road map, we list a brief description of the steps below.

1. Condition the probability distribution for use in building an aggregation distribution.
2. Prepare an aggregation distribution for the desired number of wells. From this distribution and for each desired level of certainty, determine the mean EUR.
3. Run additional Monte Carlo trials. For all trials that have the target mean EUR, tally the number of times each well from the distribution is selected. Convert this tally to a weighting factor.
4. Calculate the type well rate-time profile as the weighted average of the rate-time production profile for all wells.

The previous section, Aggregation Principles, describe the above Steps 1 and 2 in detail.

Additional Monte Carlo Trials

The objective of this step (step 3) is to determine appropriate weighting factors. With the aid of Table 1, we describe the process to determine the weighting factors.

From the aggregated distribution of mean EURs in Figure 2, the P90 mean EUR is 1010 mmcf for a group size of 45 wells. We seek to find several hundred successful Monte Carlo trials with a mean EUR of 1010 mmcf (we use a range from P89.9 to P90.1). A successful trial is one where the mean EUR falls within the specified range and the trial contributed to the determination of the weighting factor. We record a running tally of the number of times each well was in one of these successful trials. The tally for this example is in Table 1.

Because the trial selection measurement is EUR and not wells, it is necessary to replace the tally for each EUR with a weighted average of two wells having EURs that bracket the selected EUR. We reference Table 1 for the example of a selected EUR of 800 mmcf. Two wells bound this EUR: well 27 with 791 mmcf and well 21 with 836 mmcf. The tally for the 800 mmcf EUR is 0.8 for well 27 and 0.2 for well 21.

At extremes of probability, it may not be possible to bracket the desired EUR with two wells. For example, the lowest EUR in the probability distribution is 220 mmcf from well 24. We cannot bracket an EUR of 110 mmcf with two wells. In this case, we would assign a tally of 0.5 (110 / 220) to well 24.

Table 1
Weighting Factor Calculation

Well	EUR	Tally	Weight
24	220	229	5.1%
23	318	275	6.2%
22	378	136	3.1%
18	387	36	0.8%
25	398	265	5.9%
11	532	330	7.4%
10	579	182	4.1%
4	652	157	3.5%
13	653	61	1.4%
1	680	157	3.5%
19	719	291	6.5%
27	791	262	5.9%
21	836	84	1.9%
20	848	43	1.0%
8	871	244	5.5%
5	1065	268	6.0%
9	1158	83	1.9%
26	1233	75	1.7%
15	1298	271	6.1%
12	1597	176	3.9%
14	1605	28	0.6%
2	1644	185	4.1%
7	2006	192	4.3%
3	2047	105	2.3%
17	2415	85	1.9%
6	2449	115	2.6%
16	3294	133	3.0%
		4466	100%

Once we have found the desired number of successful trials and the tally is complete, the weighting factor for each well is the well tally divided by the sum of the tallies. Because the tally is the number of times each well was selected over multiple trials, it represents the probability of drilling that type of well and our objective has been fulfilled.

Calculate the type well

The last step (step 4) in the type well construction is quite simple. Multiply the production rate-time profile (prediction and history) for each well by the weighting factor and sum the result to obtain the aggregation type well.

In a previous paper (Freeborn et al.), we recommended use of the selected well method to create probability based type wells, in part because the alternative of using time slices proved to be inaccurate. In Figure 4 on the following page, we compare a type well built using the aggregation method to one using the selected well method.

The NPV comparison shows a marked difference between the two profiles. Economic evaluation of these two type wells results in a two-fold difference in 10% NPV: $378,000 using the aggregation method and $185,000 using the selected well method.

We believe that the aggregation method is more accurate when it is applied to evaluating undrilled wells because the method is statistically designed to identify the probability that a given well will be drilled. This does not imply that one should avoid the selected well method. It is perfectly suited to analog forecasting (Russell et al., 2013), where the intent is to derive a series of type wells with distinctly different rate-time production profiles.

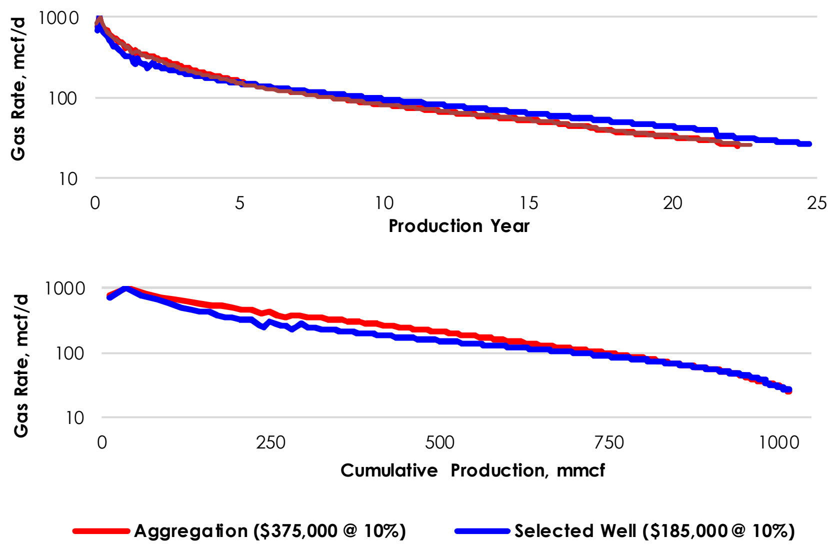

Figure 4
Wild River P90 Aggregated (35 well) Type Well Comparison

Ranking for Type Wells

We are conditioned to showing probability distributions of EUR as shown in Figure 1. When we use such a distribution to create a probabilistic type well, say the P90 well, and use that P90 type well for an evaluation, the evaluation conveys a certainty that its EUR will meet or exceed the type well EUR ninety percent of the time. This EUR distribution is suited only to assessing reserves.

When creating a type well, it is vital to have a clear understanding of the questions asked and the parameter that needs testing for certainty. A small company evaluating a prospect may count on cash flow to fund its operations; therefore, it will want to assess the certainty of its first year cash flow. A large company driven by growth in share price may want to estimate the certainty of value as approximated by EUR in equivalent barrels with a value-based conversion factor of 25:1 mcf/bbl.

A type well is not complete without an express statement of the uncertain parameter and the implied probability of achieving that parameter value. While this may seem obvious, we refer to type wells created using the time slice method (Russell et al, 2013) as an example where the uncertain parameter is unclear. The time slice method estimates the uncertainty in neither IP nor EUR. Based on production alone, it cannot quantify the uncertainty in economic parameters. One might argue that it establishes the probability of a given rate in a specific month, relative to the rate of other wells that happened to produce in the same month. Some people may have trouble understanding the meaning and relevance of this probability of the uncertain parameter; and yet the time slice method is the most commonly used by engineers and engineering software for creating probabilistic type wells.

To demonstrate the use of ranking parameters other than EUR, we present an example where we rank net present value (before capex) discounted at ten percent before tax (NPV10). The rationale is that we wish to understand the probability of our project being profitable and the reserves that could be booked. For this purpose, we use information about the Wild River wells from Figure 1.

The wells' rate-time histories and forecast were time shifted to a common start date of January 2016, and the evaluation used a current price forecast prepared by a leading Canadian reserve house.

Operating costs include estimates for fixed monthly battery costs plus variable costs for gas, oil and water. Capital costs average \$2.25 million per well.

Figure 5 shows there is a good correlation between NPV and EUR, but the variation demonstrates that well ordering by EUR (Figure 1) will differ from well ordering by NPV10 (Figure 6). Nevertheless, we would not expect much difference in the type well.

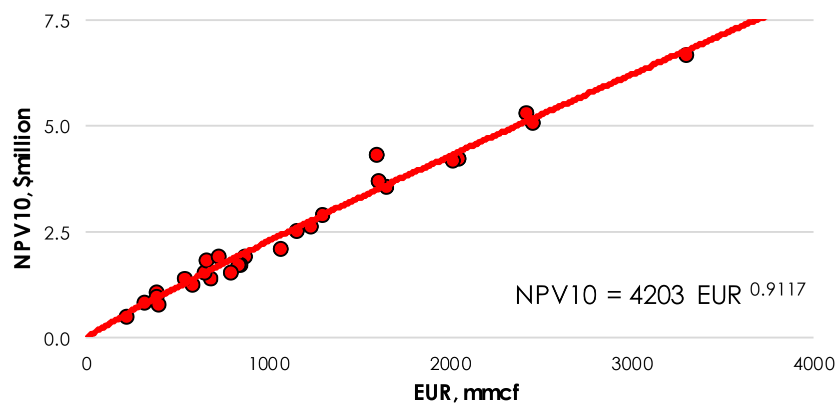

Figure 5
Wild River Correlation of NPV to EUR

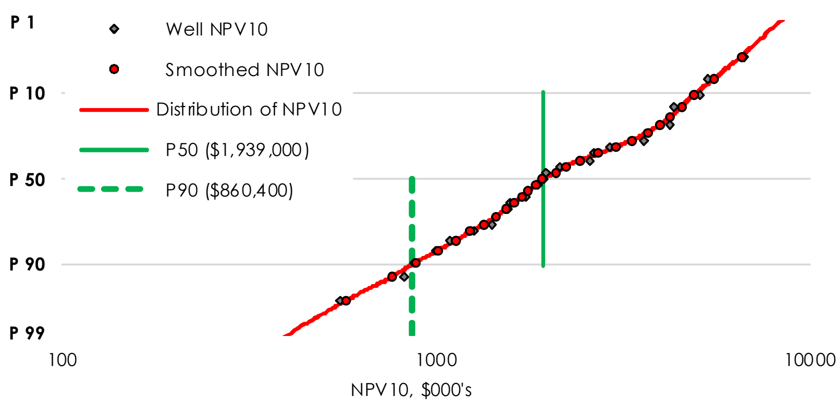

Figure 6
Wild River EUR Distribution

Figure 6 shows the NPV10 probability distribution for the Wild River wells. Because NPV10 correlates to EUR, the distribution has the same general shape as Figure 1. However, this chart offers much more information than Figure 1.

We intentionally ranked NPV10 without capital cost. In this way, we can explore the impact of different drilling costs on profitability and reserve booking. Because capital expenditures occur at the start of drilling, they are undiscounted and subtract from the NPV10 to determine the NPV10 value, net of drilling.

When the drilling cost is equal to the NPV10, the internal rate of return (ROR) is ten percent. If a minimum ten percent ROR is the economic threshold for drilling, then one could book only possible reserves. Booking probable reserves would be possible if drilling staff could reduce the cost to \$1.94 million (efficiency, improved technology or shallower wells).

To include the effects of aggregation, we would use the distribution of Figure 6 for all of the Monte Carlo calculations referenced in the Aggregation Type Wells section of this report. Thus, we calculate the weighting factors using the NPV10 distribution. Once the weighting factors are calculated, we average the merged production history and forecast as before, using the new weighting factors.

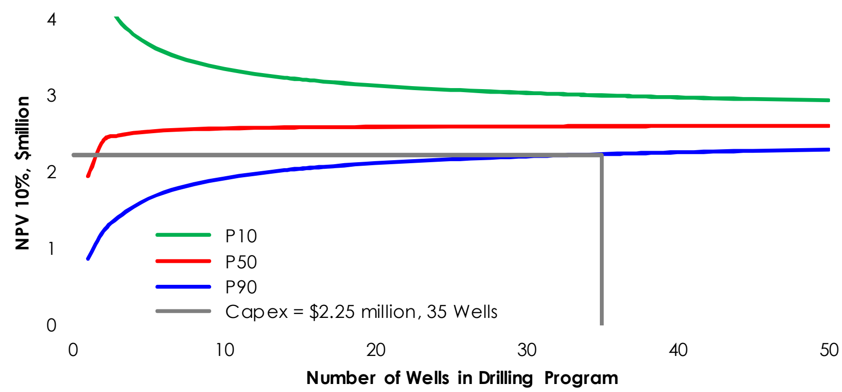

Figure 7
Wild River Aggregation Trumpet Plot

Figure 7 shows a trumpet plot of NPV10 for the Wild River wells. If the operator drilled 35 wells, the mean capital cost for those 35 wells would be $2.25 million and, by definition, the rate of return would be 10%. If this were the corporate hurdle the company would book proved, probable and possible reserves for these 35 wells from the perspective of economic viability. The chart has value because it identifies how many fewer wells would be required if the operator were able to reduce the drilling cost through a learning curve or other innovation.

This example demonstrates that we can increase the utility of type wells by establishing the probabilities of parameters other than EUR.

Scaling

The industry drills wells with different horizontal lengths and completion fluids and these wells receive different numbers of perforations and fractures. In addition, permeability variation (and fracture intensity) will result in each well commencing boundary dominated flow (BDF) at a different time. When the number of similar analog wells is small because completion parameters differ for each well, it may become necessary to adjust the rate-time profile of the analog wells to the design parameters and geology of the target wells. In this paper, we refer to these adjustments as *scaling*. We choose this term to avoid confusion with the word *normalizing* that commonly refers to time shifting and/or representing the rate-time profile in terms of dimensionless numbers.

In this section, we will propose a scaling workflow that uses three multipliers to shift the rate-time profile vertically to account for differences between the analog well and the scaled well (a scaled version of the analog). These three multipliers adjust for number of fractures, IP deterioration, and reservoir quality (permeability). In addition, the scaling will adjust for timing differences in the commencement of BDF.

Prior to interference between fractures, the reservoir near each fracture will be in linear flow and behave as a vertically fractured well with each fracture having a different flowing pressure at the wellbore. Thus, overall well productivity must be proportional to the number of fractures or equivalent vertical wells. For this reason, the first rate-scaling factor is the number of fractures in the well.

Braun et al., (2014) of Shell studied the effect of well length in the Bakken. "*The question asked of the data set was: All else being equal, to what degree are the long well productivities different from the short well productivities?*" The authors meticulously filtered data to ensure that all else was equal, narrowing their search to a single operator's twenty-seven well pairs. For example, the 9100 foot wells had double the number of fractures of the 4500 ft wells. They found that doubling the well length from 4500 to 9100 feet resulted in an increase in the IP_{180} (180-day average rate) from 371 to 596 bbl/d.

From fluid flow theory, we know that there must be a pressure drop from toe to heel of the well. Without this pressure drop, the well could not flow. Thus, the fracture at the toe will have a smaller draw down than at the heel during fracture cleanup and during production operations. We speculate that the pressure gradient can be great enough to negatively influence the fracture quality, effective fracture length and fracture productivity.

We attribute Shell's observed decrease in productivity with well length to draw down and the influence on fracture quality and geometry. Thus, we look for a correlation of IP deterioration versus well length. Since Braun et al. studied only two well lengths, we cannot determine whether the correlation is linear or non-linear. For simplicity, we choose a linear correlation as shown on Figure 8.

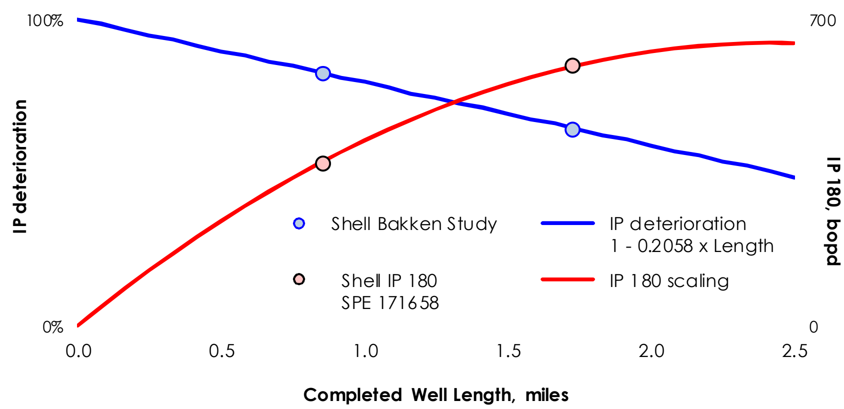

Figure 8

Impact of Well Length on Bakken Production Rate

To develop the correlation, we calculate an IP deterioration factor equal to the IP_{180} per fracture from the Shell study (two data points) divided by an assumed value for IP_{180} per fracture that has no deterioration.

We fit these two IP deterioration ratios with straight line, altering the assumed IP that has no deterioration until the correlation has a y-intercept equal to one or 100%. Also shown on Figure 8 is the calculated variation of IP_{180} versus length, calculated with the assumption that the number of fractures is proportional to the well length. This IP_{180} curve is parabolic in shape, implying a point of diminishing return for very long wells. (We recommend limiting the use of this correlation to wells less than 2.5 miles long, less than the parabolic apex of the parabola). The second rate-scaling factor is the ratio of the IP deterioration.

The third rate-scaling factor is an adjustment for reservoir quality. From Darcy's Law, rate is proportional to permeability-thickness product. Using estimates for permeability and thickness in Equation 1, we calculate the third rate-scaling factor as the ratio of productivity that would result from a difference in only the permeability-thickness product. If the pay thickness or permeability is unknown, we assume the scaling factor is equal to one. If the scaled well has production data, then we back calculate this third scaling factor to match the rates observed at the scaled well and, from this information, we may infer the difference in reservoir quality.

$$\left(\frac{IP_{180\,analog}}{IP_{180\,scaled}}\right) = \left(\frac{k_{analog}}{k_{scaled}}\right)\left(\frac{h_{analog}}{h_{scaled}}\right) \quad \ldots\ldots\ldots\ldots \; 1$$

To summarize, we can determine a composite multiplier from multiple scaling factors to scale the rate from an analog well to a well of interest.

$$\text{Rate } adjustment = \left(\frac{frac\ count_{scaled}}{frac\ count_{\ analog}}\right)\left(\frac{degradation_{scaled}}{degradation_{analog}}\right)\left(\frac{IP_{180\,scaled}}{IP_{180\,analog}}\right) \quad \ldots\ldots\ldots \; 2$$

Lee (2012) recommends that we use the equation for depth of investigation in an idealized linear system to determine the start of BDF, Equation 3. This time is proportional to the square of the fracture spacing, and to permeability. From a practical perspective, we ignore the other parameters as being much less significant. Equation 4 provides the foundation to calculate time to BDF using Equation 3.

$$t_{bdf} = \frac{1896\ \emptyset\ \mu\ c_t\ {d_i}^2}{k} \quad \text{......} \quad 3$$

Where t is in hours, μ in cp, c_t in psi^{-1}, and d_i in ft, k in md

$$t_{bdf_{scaled}} = t_{bdf_{analog}} \left(\frac{d_{i_{scaled}}}{d_{i_{analog}}}\right)^2 / \left(\frac{k_{scaled}}{k_{analog}}\right) \quad \text{......} \quad 4$$

In Equation 4, we use previous approximations to determine the permeability ratio. The permeability ratio is equal to the third scaling factor except when the ratio of pay thickness is a known parameter. In this special case, we use Equation 5 to solve for this ratio.

$$\left(\frac{k_{analog}}{k_{scaled}}\right) = 3rd\ scaling\ factor \left(\frac{h_{scaled}}{h_{\ analog}}\right) \quad \text{......} \quad 5$$

Scaling Example

We will use several older Montney wells from the Heritage field in British Columbia, Canada to demonstrate and test the proposed scaling algorithm. Data for the selected wells are in the public domain, and fracture data is available. The wells are in close proximity to one another. Parameters used for the scaling are in Table 2. We also use Table 2 to present the scaling parameters that resulted from using the diagnostic benefits of the scaling algorithm discussed later in the paper.

Table 2
Summary of Well Parameters for Scaling

	Fractures			Completed Length				IP Deterioration		Scaling Factors			
Before Diagnostics	No. of Fracs	Frac Spacing ft	Frac Size tonne	Well Length ft	No. of Perfs	Toe Perf ft	Heel Perf ft	IP 180 mcf/d	Well Factor	#1 fracs	#1 IP	#3 kh	#4 tbdf
02/11-13-077-15W6/0	9	825	n/a	6599	9	14736	8136	1979	0.743				
00/05-13-077-15W6/0	5	1542	1100	6170	15	14437	8268	1882	0.760	0.556	1.023	1.000	0.309
00/10-13-077-15W6/0	16	492	1581	7375	16	15380	8005	3196	0.713	1.778	0.959	1.000	3.160
00/01-14-077-15W6/0	8	755	n/a	5287	8	13161	7874	1447	0.794	0.889	1.069	1.000	0.790
After Diagnostics													
00/05-13-077-15W6/0	8	881	1100	6170	15	14437	8268	2526	0.760	0.889	1.023	1.350	0.585
00/10-13-077-15W6/0	7	1229	1581	7375	16	15380	8005	5481	0.713	0.778	0.959	2.750	0.220
00/01-14-077-15W6/0	8	755	n/a	5287	8	13161	7874	4111	0.794	0.889	1.069	1.200	0.658

Scaling – Analog Well

Well 02/11-13-077-15W6/0 is the analog well that we will scale to approximate the rate-time profile of the other wells. It is the oldest of the wells, first producing in 2007, and has nine perforations and nine plug-and-perf fractures. The distance between the heel and toe perforations is 6599 feet, resulting in an inter-fracture distance of 825 feet.

The best fit of rate-time data is a modified hyperbolic equation with exponent of 2.3, switching to a low exponent hyperbolic (b = 0.3) when the nominal decline rate reaches 0.14.

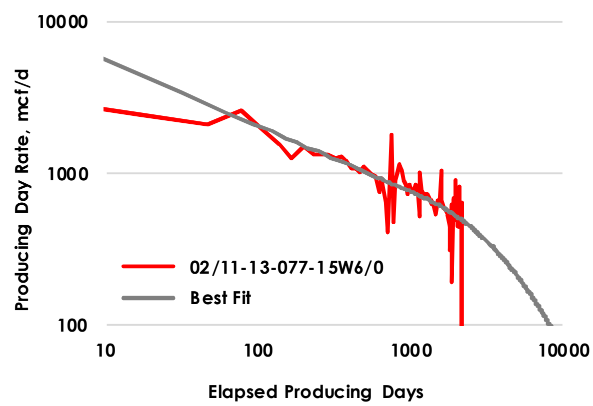

Figure 9

Best Fit for Analog Well 02/11-13-077-15W6/0

We designed Figure 9 and subsequent plots to show well capability by plotting producing day production rate (monthly volume divided by the number of producing days in the month). This requires adjustment of the time scale to cumulative producing days to preserve material balance. This method of plotting will prevent shut-in time from distorting the comparison.

Scaling – Example 1

Well 00/05-13-077-15W6/0 is the first well to test for scaling. The completion had five fracture stages with three perforations per stage (four in the heel). The perforations were acidized but there were no diverting agents to assist in placing fractures in all perforations. Figure 10 shows the scaled production profile with the actual production history reported for the well.

Scaling used one fracture per stage and no adjustment for permeability-thickness. The completion successfully placed 205 tonnes of proppant per stage, except for the heel stage that received 280 tonnes. This proppant volume is approximately double the amount used in a normal Montney fracture.

In Figure 10, it is apparent that the scaling for this well does not result in a match of the production history. This does not necessarily mean the scaling does not work, but may mean that the geometry of the well and fractures differ from our expectations. We tried some back calculations to gain insight from this example.

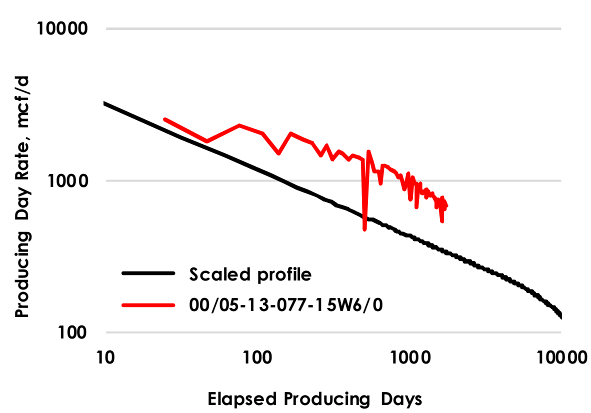

Figure 10

Scaling for Well 00/05-13-077-15W6/0

Because the completion used perforation clusters, there could be as many as sixteen fractures in this well. The largest number of fractures that could be open and still match the production history is twelve, shown as a dotted blue line in Figure 11. With twelve fractures, the onset of boundary-dominated flow is too early, implying that there must be fewer fractures.

The 5-13 well is 1320 feet from the analog, so we would expect that the matrix permeabilities and pay thicknesses would be similar. However, we also know that several stages would have received abnormally large fractures, creating larger effective permeabilities. Scaled production rates would match historical rates if the scaled well permeability were 2.2 times larger than in the analog. We know this is too large because the onset of boundary-dominated flow in the scaled well is too late.

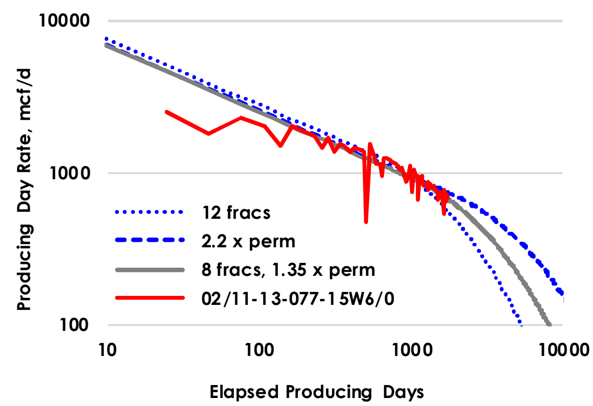

Figure 11

Alternate Scaling for Well 00/05-13-077-15W6/0

We obtain the best result by scaling with eight contributing fractures and a 1.35 fold greater permeability thickness. If this scaling is correct, it provides great insight.

In this case, one might assume that cluster fracturing (multiple perforations per fracture stage) was detrimental. Our best solution indicates:

- Some fractures are missing. Their absence would likely result in lost recovery from the well.
- With only a single fracture in a stage, the fracture volume would be double the normal design, and the fracture may be too long for proper cleanup. This is not cost-effective.
- Higher production rates may have been possible with a ten-interval plug-and-perf completion.

A cynic would suggest spending efficiency would improve with ten plug-and-perf fractures: the same material cost, little difference in time and improved performance. We test this conjecture in the scaling model with ten fractures and no enhanced effective permeability. The results, shown in Figure 12, suggest that performance from the cluster fracturing were superior.

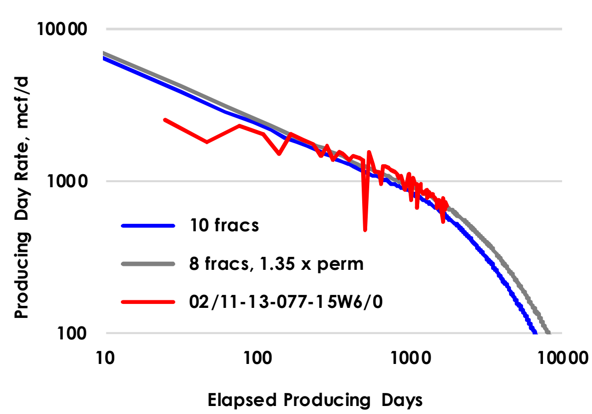

Figure 12

Alternate Scaling for Well 00/05-13-077-15W6/0

Scaling – Example 2

The second example well is 00/10-13-077-15W6/0. The well is 2640 feet from the analog and has sixteen fractures and perforations. Perforation and fracturing used Cobra Max technology with sand plugs. The completion placed about 100 tonnes of proppant per fracture. The well length is 7375 feet, which would result in an inter-fracture distance of 492 feet. This inter-fracture distance, sixty percent smaller than in the analog, results in earlier commencement of boundary-dominated flow, as shown in Figure 13. We also see that the scaled production profile has rates lower than measured, implying that the effective permeability-thickness must be larger than in the analog.

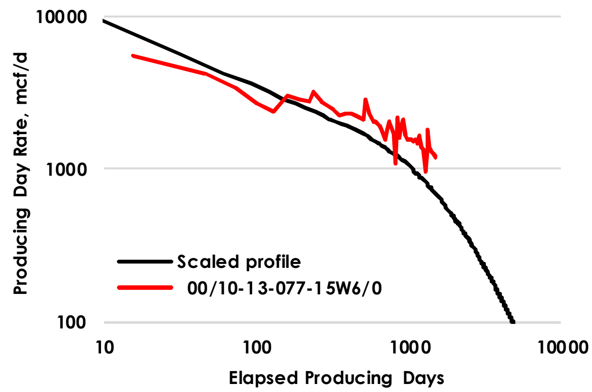

Figure 13

Scaling for Well 00/10-13-077-15W6/0

As before, we alter the scaling parameters to gain insight into the abnormal performance of this well and show the results in Figure 14.

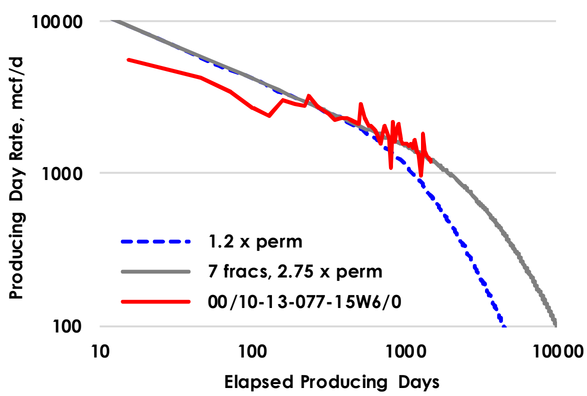

Figure 14

Alternate Scaling for Well 00/10-13-077-15W6/0

We first increase the permeability-thickness to 1.2 times the analog to match the production rate, while retaining sixteen fractures. As shown by the dashed blue line, the early rates match, but the start of boundary-dominated flow is still not correct. We must reduce the number of fractures and offset the resulting rate reduction with a greater permeability-thickness multiplier. After repeated trials, the best possible match to the measured 10-13 production profile is to scale using 7 fractures and a permeability multiple of 2.75 as shown by the grey line in Figure 14.

How could such bizarre behavior occur? If some of the fractures were ineffective, the time to boundary-dominated flow would be greater, but the rate would be lower. A possibility is that fractures inter-connect behind pipe such that the average inter-fracture distance is larger. The productivity per fracture improves because the existing fractures have increased the cross-sectional area with greater effective permeability.

As with example 1, the scaling mechanisms appear to be working as intended, but they are not predictive because the geometry of the scaled well appears to be much different from the available data. The diagnostic capability of the scaling algorithms is still quite useful.

Scaling – Example 3

The third example well is 00/01-14-077-15W6/0, located 2640 feet from the analog well. The completion consisted of eight fractures for eight perforations. The amount of sand placed is not in the public domain. The well is 5287 feet long and has an inter-fracture spacing of 755 feet.

Figure 15 shows the scaled rate-time profile for this well. It is a good match to the example well's production history, demonstrating that the scaling algorithm is predictive for a well that is 80 percent shorter with fewer fractures.

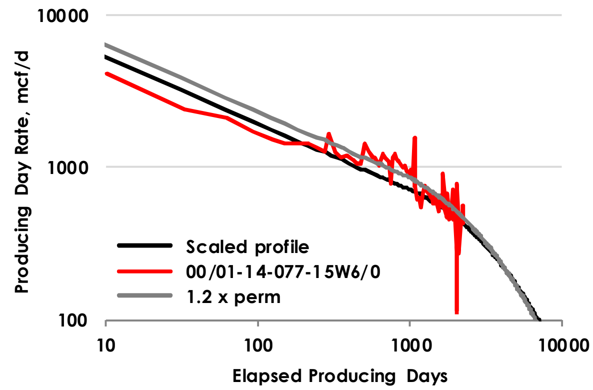

Figure 15

Scaling for Well 00/01-14-077-15W6/0

The scaled rates are slightly too low and should be adjusted by scaling the permeability thickness up by 20 percent.

Scaling – Summary

Scaling is useful as a diagnostic tool and as an adjustment tool; both uses are equally powerful.

As a diagnostic tool, we look for producing wells where the scaling appears to fail. This indicates that the planned and executed completion programs differ from one another. Scaling then serves to diagnose the difference by testing alternate scaling parameters. With this diagnosis, we will understand the possible causes for different rate-time performance between the analog and the diagnosed well, allowing us to optimize completions and improve project profitability.

It would be perfect if every (source) well used to construct a type well had the same completion (number of fractures), geometry (well length) and reservoir quality (permeability) as the design parameters for new wells that will use the type well as an analog. With known conditions in the source wells, we can achieve this perfection using scaling as an adjustment tool.

Estimating the time to the start of boundary-dominated flow is the greatest uncertainty that engineers face when forecasting the rate-time profile for unconventional wells. Scaling a well that has produced long enough to be in boundary-dominated flow is a useful way to extend this information to forecasting newer wells that are still in linear flow. If a well with boundary dominated flow is not available, then one may create an analog using advanced analytical methods.

Cluster fracturing, where a single fracture treatment acts on multiple perforations, is becoming a standard operation. With this completion style, the total number of fractures is unknown. We have shown with examples that scaling from an analog with known fracture geometries may help quantify the rate-time production profile for the cluster-fractured well and help identify the number of contributing fractures. This added insight comes without the cost and manpower of simulation and rate-time analysis.

The Last Word

In this paper, we have shown powerful techniques: aggregation forecasting, probabilistic forecasting using distributions of variables other than EUR, and scaling. Statistical principles, engineering correlations and logic are the foundation for these techniques.

Aggregation type wells accurately simulate the average rate-time production profiles expected from a drilling program of specific size and certainty. This method of constructing type wells is not restricted to unconventional resources. Using this proposed type-well construction method, the evaluator has answers to his or her questions:

1. Which wells should I use to build my type well?
2. Do I need to weight the wells differently?
3. How do I incorporate correct probabilities?

With aggregation forecasts, the probability distribution can be that of any parameter of importance. We illustrated the power of disconnecting the probability distribution from the type well creation using an economic parameter, discounted net present value. A probability distribution of other parameters such as first year cash flow may also prove useful.

We built a set of rules for scaling a rate-time profile that considers the number of fractures, deterioration of productivity with well length, permeability-thickness product and time to boundary dominated flow. The results of examples show that the scaling rules can be a powerful diagnostic tool when scaling a well with certain completion geometry to a well for which the geometry is not well known.

The scaling rules are also useful in adjusting performance to known fracture count, well length and assumed permeability. In this way, all of the wells used to build the aggregation type well will have the design parameters of the new wells.

Operators are encouraged to use aggregation for calculating and reporting proven reserves. This practice will lead to larger volumes of reserves and a more informed shareholder.

References

1 Braun, D, Powell, B, Guo, R, Morad, K., 2014. Entering a Liquid-Rich Shale Play Development Best Practices. Presented at the SPE/CSUR Unconventional Resources Conference, Calgary, 30 October-1 November 1, 2014. SPE 171658.

2 Freeborn, R., Russell, B. and Keinick, W., 2012. Creating Analogs, Fact and Fiction. Presented at the SPE Hydrocarbon, Economics and Evaluation Symposium, Calgary, Canada, 24-25 September. SPE 162630.

3 Hall, R., 2013. Short Course I: Monograph 3 Training. SPEE Course presented at the 2013 SPEE Annual Meeting, Coeur d'Alene, Idaho, USA, 9 June.

4 Haskett, W. 2005. Production Profile Evaluation as an Element of Economic Viability and Expected Outcome. Presented at the SPE Hydrocarbon, Economics and Evaluation Symposium, Dallas, Texas, USA, 3-5 April. SPE 90440.

5 Lee, Dr. J., 2012. Reservoir Engineering Aspects of Unconventional Resources. SPE Course presented at the SPE Unconventional Resource Conference, Calgary, Canada, 29 October.

6 Russell, B., Freeborn, R. and Keinick, W. 2012. A practical Guide to Unconventional Petroleum Evaluation. Presented at the SPE APOGE Conference, Perth, Australia, 24-25 October. SPE 158867.

7 Russell, B. and Freeborn, R., 2013. A Practical Guide to Unconventional Petroleum Evaluation Part 2. Presented at the SPE Unconventional Resource Conference, Calgary, Canada, 5-7 November. SPE 167215.

8 SPEE, 2010. Monograph 3 – Guidelines for the Practical Evaluation of Undeveloped Reserves in Resource Plays.

9 Sutton, R., Cox, S and Barree. 2010. Shale Gas Plays: A Performance Perspective. Presented at the SPE Tight Gas Completion Conference, San Antonio, Texas, UAS, 2-3 November. SPE 138447

10 Vanorsdale, C., Evaluation of Devonian Shale Gas Reservoirs. SPE Res Eng, May 1987.

11 Wikipedia. 2015. Monte Carlo method (19 May 2015 revision), http://en.wikipedia.org/wiki/Monte_Carlo_method.

Biographies

Randy Freeborn is Chief Research Engineer for Energy Navigator Inc., a software company that specializes in reserve evaluation and AFE management. He has been with the company for 8 years and has over four decades of petroleum engineering experience. Freeborn is a subject matter expert in decline curve analysis, automatic forecasting, and type wells and routinely speaks on these topics at conferences and luncheons. He holds a degree in mechanical engineering from the University of Calgary and is a registered Petroleum Engineer in Alberta. Freeborn is a member of SPE and SPEE, and is an SPE Distinguished Lecturer.

Boyd Russell is the President and Founder of Energy Navigator Inc., a software company that specializes in reserve evaluation and AFE management Boyd is an accomplished reservoir engineer and has extensive experience in reservoir engineering, engineering software development, property evaluations, and reserves evaluation. Boyd is a member of APEGGA, SPE and SPEE. In the last few years, Boyd has authored or co-authored several papers and has given many presentations on Unconventional Reserve Evaluations, Decline Analysis, Type Wells and Analog Forecasting. Boyd is a graduate from the University of Alberta in petroleum engineering.