Volver

A Practical Workflow for Performance Prediction of Low Permeability Reservoirs

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Introduction

The Society of Petroleum Evaluation Engineers (SPEE) recently released Monograph 4, "Estimating Ultimate Recovery of Developed Wells in Low-Permeability Reservoirs" (hereinafter called "Monograph 4"). This paper outlines a practical engineering workflow enabling companies to evaluate unconventional plays developed with horizontal multi-stage fractured wells consistent with the principles summarized in Monograph 4. This workflow has many applications including assessing potential acquisitions, defining new plays, evaluating competitor results, corporate budget processes, long term business planning, portfolio management, or reserves certification.

The workflow is based on the recognition that reservoir performance and reservoir behavior are two separate things. Reservoir behavior is driven by the rock and fluid properties (fluid type, permeability, relative permeability, compressibility, PVT data, etc), and can be largely characterized by the decline exponent, or shape of the curve. Within an area exhibiting similar reservoir behavior, we see variations in reservoir performance, which can be associated to many factors including completion type, completion effectiveness, and minor variations in reservoir quality within the area.

The workflow begins with determining "geologic bins" within the study area (based on similar reservoir behavior), then assessing the production performance exhibited by wells within the bin. Standard empirical decline curve analysis (DCA), using a two-segment Arps equation, is employed to estimate (1) a representative decline exponent in the initial transient flow period, (2) the time to boundary dominated flow, and (3) a representative decline exponent in the boundary dominated flow period. This initial assessment of reservoir behavior is followed by further segregation of the wells into "performance bins", respecting local variations in reservoir quality affecting productivity and estimated ultimate recovery. Typical production performance profiles (type curves) are created for each of the performance bins. The type curves are used to forecast the future production for existing wells and future development.

This workflow has been developed and refined over several years, and has been tested in large scale applications. Two case studies are presented demonstrating the capabilities of the process. A third example is referred to throughout the paper to illustrate the principles and procedures.

Reservoir Characterization

Reservoir behavior is influenced by the geology and fluid properties of the reservoir. The workflow presented in this paper relies on analyzing groups of wells with similar reservoir behavior. The process begins with identification of geologic bins consisting of wells that produce from reservoir rock with similar in-situ reservoir characteristics and fluid types. While a fulsome discussion on reservoir characterization is beyond the scope of this paper, having a full understanding of the geologic characteristics of the reservoir being developed is critical to identifying these geologic bins. It has been our experience that minor changes in geologic parameters and reservoir fluids do not significantly affect reservoir behavior; however, depositional environment or fluid phase are factors that require different geological bins. By way of example, the Viking Formation in Saskatchewan, Canada covers approximately 70 townships (1,613,000 acres, or 653,000 hectares) and, with a relatively consistent depositional environment, does not require geologic binning to analyze the 4500+ horizontal wells. The only differentiation required is between oil wells and gas wells. Conversely, the Cardium Formation in Alberta, Canada (covering an area of approximately 200 townships, or 4,608,000 acres, or 1,865,000 hectares) consists of multiple depositional environments and fluid types (ranging from black oil transitioning into wet natural gas). In this case, we have defined ten geological areas with many areas further sub-divided based on fluid type into Oil, High GOR Oil, and Gas. Lacking production data, the geologic bins can be created from a detailed reservoir characterization analysis. With production data available, the geologic bins can be verified with the Flow Regime Diagnostics discussed in the following section.

Flow Regime Diagnostics

Production performance from horizontal, multi-stage fractured wells in low permeability reservoirs is typically characterized by multiple, identifiable flow regimes. These characteristics are ably represented by a simplified assumption of two distinct flow regimes (Lee 2007), with a transitional period between them. Initially, a well produces in transient flow, where the area of investigation continues to increase. Typically, the well is expected to exhibit linear fracture flow behavior. The familiar transient solution, linear fracture flow equation is capably represented by the hyperbolic Arps equation with a decline exponent of 2 (Okouma 2012). For the purpose of this paper, we will refer to the transient flow period as the linear flow period. As the area of investigation increases, no-flow boundaries are encountered and the pressure decreases across the entire drainage area, as illustrated by Figure 1. This indicates the beginning of pseudo-steady state flow, also called boundary dominated flow (Lee 2007). From the time that portions of the well bore and its fracture system produce against the first no-flow boundary until the last no-flow boundary is encountered, the well goes through a transitional period.

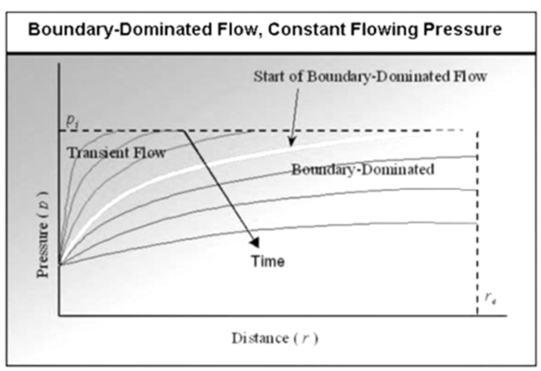


Figure 1 - Schematic showing Pressure versus distance from wellbore, at various times, illustrating when transient flow transitions to boundary dominated flow (Fekete 2012a)

Flow regimes can be identified using a log-log rate-time plot, where a half slope indicates linear flow, and a slope steeper than a unit slope indicates boundary dominated flow (unit slope indicates harmonic flow), as shown in Figure 2.

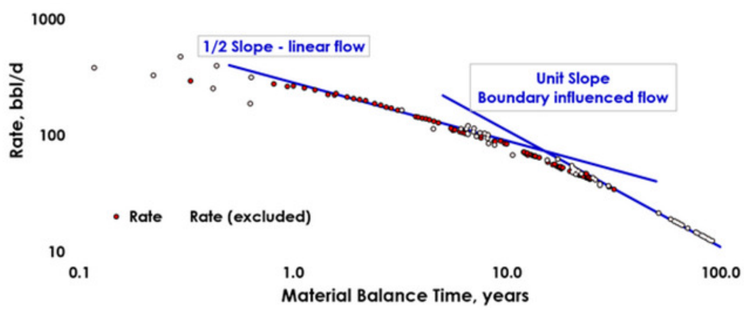


Figure 2 - log of rate versus log of time plot shows how the linear flow period and boundary dominated flow period can be identified (Fekete 2012b)

By making a simplifying assumption to the Arps equation, we can calculate the Arps decline exponent (commonly shown as either ‘b’ or ‘n’). The equation below rearranges the Arps equation and takes the log of both sides:

$$q = q_o(1 + bDt)^{-1/b}$$

$$\log(q) = \log\left[q_o(1 + bDt)^{-1/b}\right]$$

If we assume that bDt >> 1, we can further rearrange the equation as such:

$$\log(q) = {-1}/{\mathrm{b}}\,\log(q_o bDt)$$

$$\log(q) = \frac{-\log(q_o bD)}{b} - \frac{\log(t)}{b}$$

$$\underbrace{\log(q)}_{\text{Y}} = \underbrace{{-1}/{b}}_{\text{slope}}\,\underbrace{\log(t)}_{\text{x}} \underbrace{- \frac{\log(q_o bD)}{b}}_{\text{y-intercept}}$$

When plotting log rate versus log time, the negative inverse of the slope is the decline exponent. However, the simplifying assumption has implications which must be taken into consideration when relying on the resultant calculation.

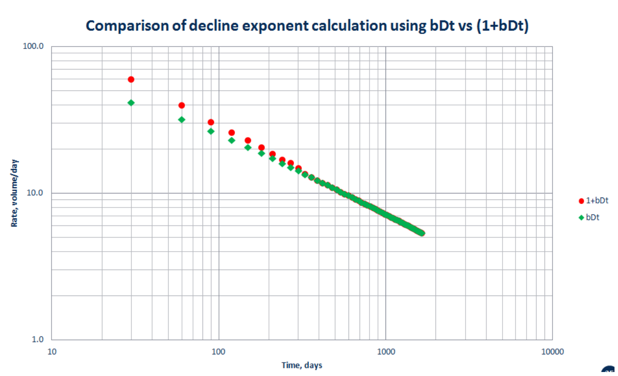


Figure 3 - Error created by the simplifying assumption can be seen in the first five to ten data points

From Figure 3, we can see that the first several points may be misleading when the assumption that bDt >> 1 is not valid. But, keeping this in mind we can calculate the decline exponent for the linear flow period, estimate the time to boundary dominated flow, and calculate the decline exponent of the boundary dominated flow period, given enough data.

Figure 4, Figure 5 and Figure 6 present examples of the log-log rate-time plot being utilized to calculate the decline exponent. Unit slope, half slope, and quarter slope reference lines appear on the bottom left portion of each of the plots as a tool to visually gauge the slope of each line.

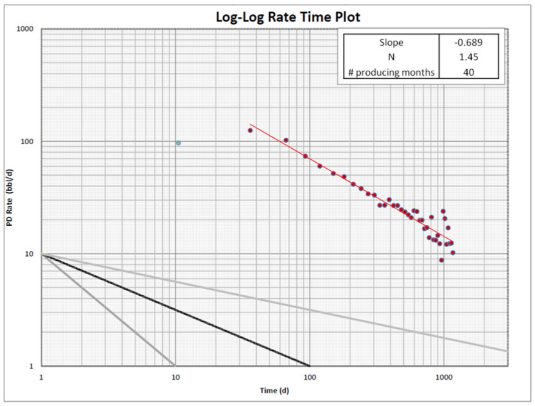


Figure 4 - log rate versus log time plot showing b value calculated at 1.45

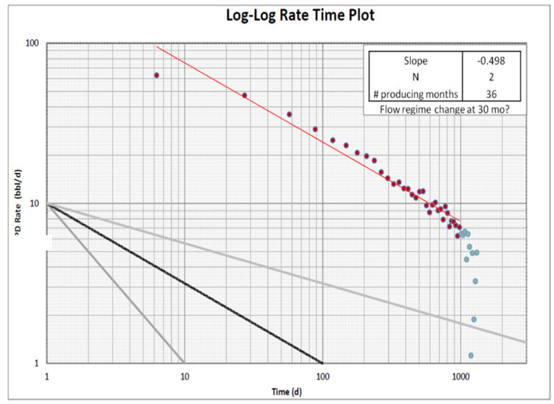


Figure 5 - log rate versus log time plot showing effect of early data points. By not excluding the early data points, the best fit slope is shallower than it should be, producing a b value higher than actual

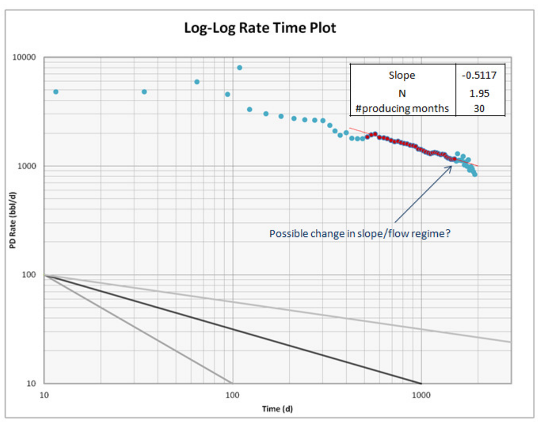


Figure 6 - log rate versus log time plot showing possible boundary effects after 30 months of production

Like all analysis on real well data, non-representative or “scatter” data requires quality assessment and filtering. This includes data points that do not fall along the trend of other points (Figure 7), or entire data sets from wells that are being rate restricted or are not producing at the reservoir’s capability (Figure 8). There are other methods to evaluate the type of wells that would be excluded, but those discussions are beyond the scope of this paper. Monograph 4 discusses some of these techniques.

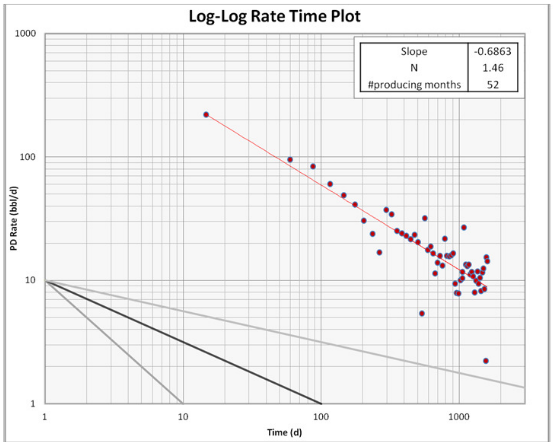


Figure 7 - log rate versus log time plot showing scattered data. The outlying data points should be excluded from this analysis

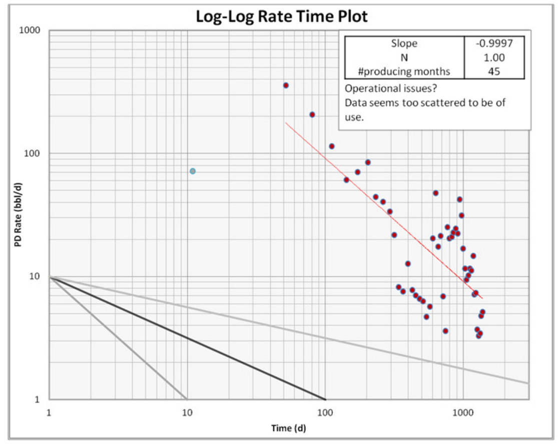


Figure 8 - log rate versus log time plot showing scattered data. This well should be excluded from the analysis

As we start to analyze the flow regimes of multiple wells, we will notice that all wells do not display the same decline exponents or time to boundary dominated flow. This is expected, as each well is draining a portion of the reservoir with slightly different reservoir characteristics. If all wells showed exactly the same characteristics, we would expect to see the exact same production profiles and expected ultimate recovery (EUR), and we know that this isn't reality. When examining the EURs of many wells within a geologically analogous area, we expect to see a range of results that fall on a log-normal distribution (Brown 2001), and we expect a similar distribution of decline exponents. Figure 9 and Figure 10 show example distributions of decline exponents.

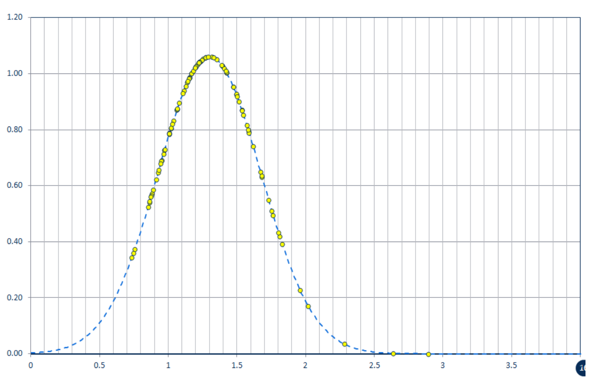


Figure 9 - Distribution of decline exponents, shown on normal distribution

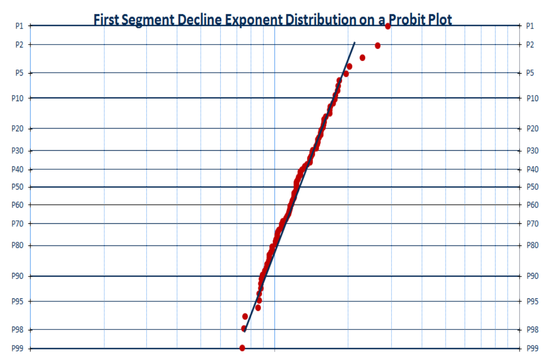


Figure 10 - Distribution of decline exponents, shown on probit scale plot. Most of the points fit very well on the lognormal distribution, but the top 3 points seem to deviate from the trend.

Comparison of the actual to expected distribution may be used as a diagnostic test of the geologic binning process. Deviation from a straight line on a probit scale plot may indicate that the data set represents significantly varying reservoir characteristics within the bin (Figure 13). In this case, it might be worthwhile considering whether the geologic bin should be further sub-divided. Excessive P10/P90 ratios (> 10) may also indicate a need to further sub-divide the bin (Figure 11 and Figure 12).

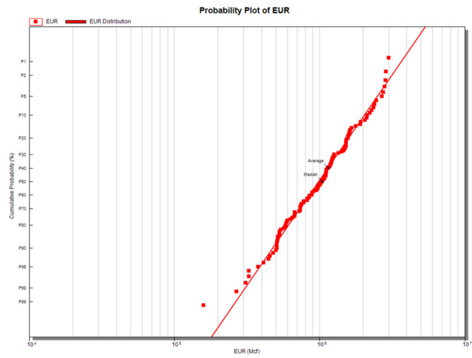


Figure 11 - Probit plot, data lies within lognormal distribution, P10/P90 ratio = 4

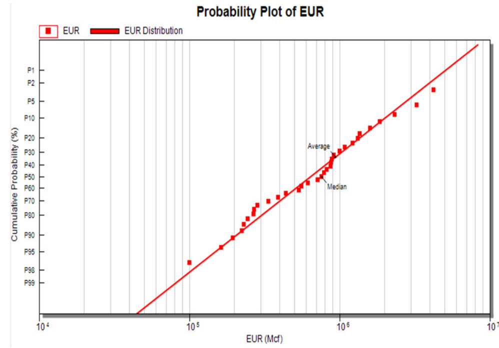


Figure 12 - Probit plot, data lies within lognormal distribution, P10/P90 ratio = 10

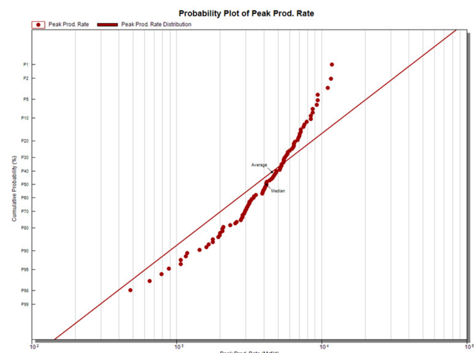


Figure 13 - Probit plot, data does not lie within lognormal distribution. Data set may be coming from more than one geologically analogous area

When performing this work on a statistically relevant number of wells in a play, we can determine the range of decline exponents that can be expected in the linear flow period. Additionally, a range of how long we expect the linear flow period to last can be estimated, given enough data. In the case where production history is limited and wells have not seen boundary effects yet, we can at least get an estimate for the minimum amount of time that wells are staying in linear flow. Using that data and our experience in other similar plays we can make a judgment on the length of time that we expect an average well to stay in linear flow. When this analysis is complete we have the ability to predict average parameters for new wells as they commence production, even though we do not yet have enough data to determine the decline exponent for that particular well or the length of time it will be in linear flow.

Determining the decline exponent for the boundary dominated flow period can be more challenging as it requires a significant amount of production history in the boundary dominated flow regime, which is often not available in newer plays. However, given a lack of data, we can examine older vertical wells producing out of the same formation, if they exist, to estimate the decline exponent or use modeling methods to predict what it may be. This same type of analysis on offset vertical analysis or through modeling, can also be used to determine an appropriate minimum decline rate (D_{min}), where the boundary dominated flow forecast transitions to an exponential Arps forecast.

Creating Typical Performance Curves

A typical performance curve, or type curve, is a statistical representation of the typical performance of an idealized or average well. Type curves are one of the most widely used tools used to analyze low permeability plays, and are an integral part of this workflow. Based on the fundamental principle that reservoir behavior and reservoir performance are different things, we can then create our type curves based on wells with like reservoir behavior, rather than having to identify different drilling methods, different completion fluids, different completion techniques, etc., before determining which wells should be included in the type curve process. Rather, we can include all wells within the geologic bin in the type curve process. The advantage of this is that we do not have to break up the wells into bins with a number of wells that are statistically insignificant, especially when the completion techniques have been evolving over time. Additionally, we do not run into the argument that the type curves are no longer relevant because a different completion technique is now being used. By using all of the wells within the geologic bin, we can maximize the statistical significance of each of the type curve bins, yet still capture the variations in parameters at different performance levels.

The workflow involves creating "performance bins" within each of the geologic bins, which can be done in several ways depending on the dataset being analyzed. The first step is to determine how the performance of the wells within a particular play is going to be classified. To do this we can examine the relationship between early-life key performance indicators, such as one-month maximum rate, initial 30-day rate, initial 90-day rate, or six month cumulative production, versus longer term performance indicators such as 12-month cumulative production or 18-month cumulative production (Figure 14, Figure 15 and Figure 16).

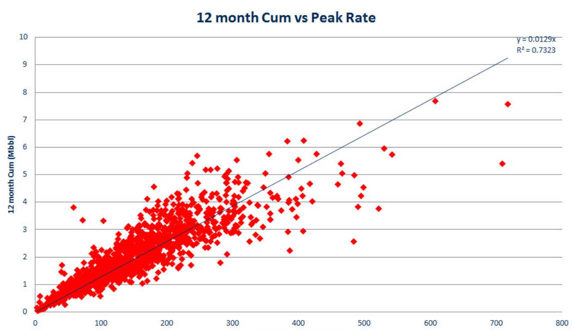


Figure 14 - Max peak rate versus 12 month cumulative production, quite scattered

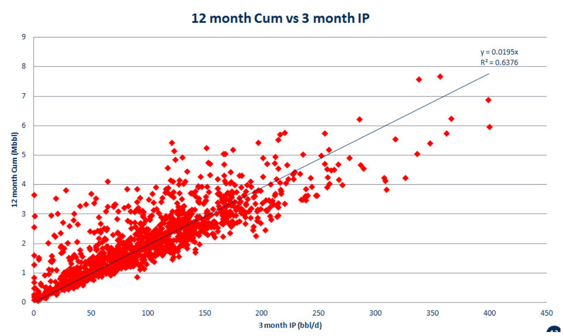


Figure 15 - 3 month initial rate versus 12 month cumulative production, still quite scattered

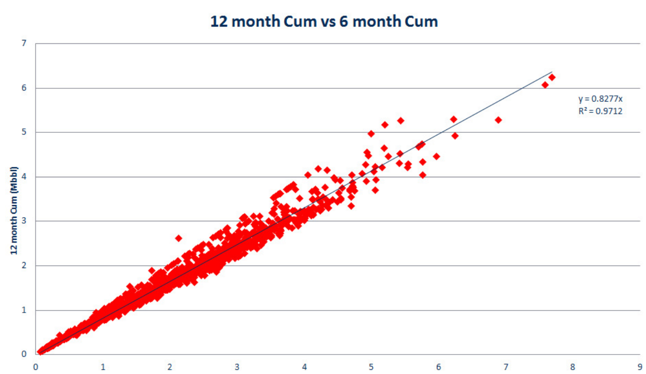


Figure 16 - 6 month cumulative production versus 12 months cumulative production, very good correlation

By looking at these relationships, we can tell which parameters are most indicative of longer term performance, and base our performance binning on the most appropriate parameter.

With large datasets, we expect a more complete distribution of results so there is less intervention required than with smaller datasets. Large datasets can usually be split into five to ten equal sized bins, based on sorting the wells by the appropriate performance indicator. For smaller datasets, the same type of process can be done, but consideration needs to be paid to whether fewer bins need to be made due to sample size, or whether bins need to be made with different number of wells due to natural breaks in the sample set.

With the wells broken into performance bins, the type curves can be generated. Freeborn and Russell (2012) discuss best practices of creating type curves, the main one being that type curves should be created using historical data plus forecast data for all wells, rather than just historical data. While adding forecasts to each well introduces a level of bias based on the production profile forecast for each well, that bias has a much smaller influence and impact than the "survivor bias" created by using only historical data (Figure 17).

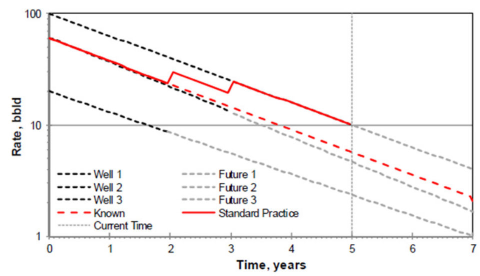


Figure 17 - Fundamental of Survivor Bias as presented by (Freeborn and Russell 2012)

The first step in creating type curves for each performance bin is to forecast the production of each well, based on the parameters determined when performing the flow regime diagnostics. We previously determined the average decline exponent for the group of wells in both the linear flow period and the boundary dominated flow period, and have estimated the time to boundary dominated flow. With this information, we can match up the current initial rate for each well, adjust the decline rate to match the actual historical production, transition to the lower decline exponent for boundary dominated flow, and run the production out to a reasonable technical limit for the particular play (applying a D_{min} if necessary). The transition from the linear flow period to boundary dominated flow should be smooth, meaning the decline rate right before the transition is the same as right after the transition. There should be no kinks in the curve (illustrated in Figure 18, Figure 19 and Figure 20).

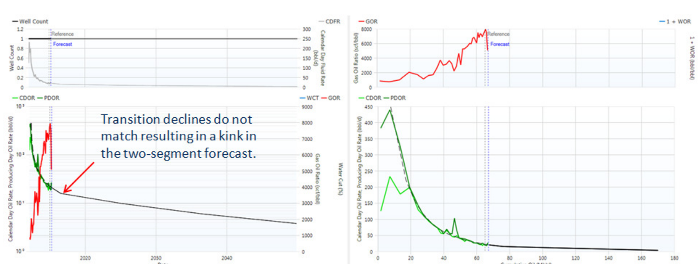


Figure 18 – Example of a transition where the decline rate at the start of boundary dominated flow is lower than the decline rate at the end of linear flow, leading to a kink

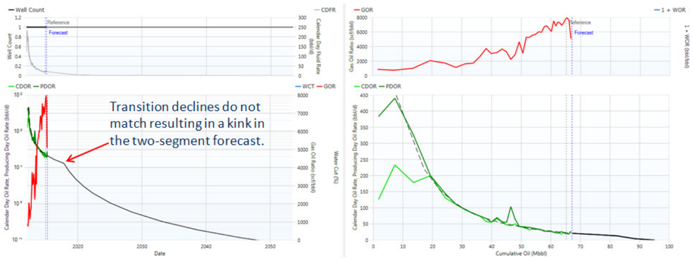


Figure 19 - Example of a transition where the decline rate at the start of boundary dominated flow is higher than the decline rate at the end of linear flow, leading to a double-dip

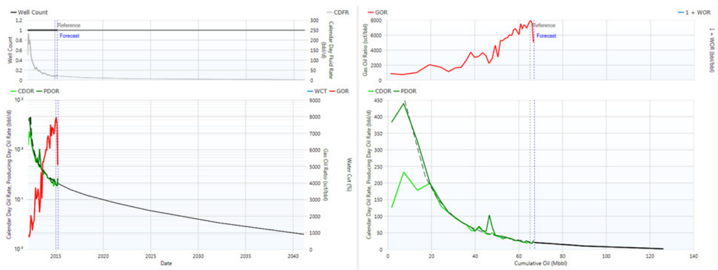


Figure 20 - Example of a transition where the decline rate at the start of boundary dominated flow is equal to the decline rate at the end of linear flow, leading to a smooth transition

We know from the work done in flow regime diagnostics that all that not all wells display the same linear flow decline exponent and time to boundary dominated flow, but in this process we are assuming the same average parameters for all of the wells. To increase accuracy, each well could have the decline exponent set to match its particular data, and the time to boundary dominated flow could be adjusted to match the data distribution, assuming that there is enough data to be able to determine when the transition occurs. However, in our experience doing this type of well-by-well work results in a very similar overall answer, making the additional analysis immaterial. By using the average parameters, some wells will be a bit optimistic, while others are a bit pessimistic, and the overall average performance curve is close to the same as when the detailed work is performed. Each evaluator needs to balance the amount of time available for the analysis with the need for precision and decide how much work is necessary in this step for their particular situation.

With all of the wells forecast, a type curve can be created for each of the performance bins. This is done by normalizing all of the wells to a maximum production rate as time zero, then averaging the rate for each production period (usually month) for the life of the dataset. This averaged production profile can then be approximated by a two-segment Arps forecast, following the same parameters that were determined earlier in the flow regime diagnostics.

There are other methods to forecast the linear flow period, such as the Duong or Stretched Exponential models, which are discussed in detail in Monograph 4. Neither of these are perfect solutions, as they are still only valid for the linear flow period and have to transition to the Arps equation for forecasting the boundary dominated flow period (SPEE 2016). We have chosen to use the 2-segment Arps method (also known as Modified Arps) as it ties into the various parts of the workflow very efficiently. Specifically, the flow regime diagnostics are designed to work with the Arps equations, and most commercial software available is designed to work with the 2-segment Arps method.

We have chosen to ignore the transitional flow period (which would result in a 3-segment Arps method) by assuming that the transition from linear flow to boundary dominated flow happens instantaneously halfway through the transitional flow period. This assumption was derived from sensitivities performed on ultimate recovery and net present value comparing these 2 methodologies. The sensitivities showed a minimal difference when assuming a 2-segment Arps rather than 3-segment Arps forecast.

Each evaluator can choose to use a different forecasting method (Duong transitioning to Arps, Stretched Exponential transitioning to Arps, or 3-segment Arps, etc) in this workflow if they choose to. We have found that the results tend to be very similar when applying the same transition to boundary dominated flow, so we recommend using the most efficient methodology with the software available.

Several different commercial software packages have been designed to assist with this process, making it much more efficient than it would be were this to be done manually. For example, performing the work described in this section of the paper for several thousand wells across nine performance bins takes hours using available commercial software, versus days or even weeks were it to be done manually.

The result of this work will yield a series of type curves for the play spanning a range of performance bins indicative of the actual performance range seen in the play. It is expected that as the performance increases, the initial decline rates also increase (ie with higher initial rates comes steeper initial declines, Figure 21). The implication is that a 1:1 relationship between initial rates and ultimate recoveries is not observed. That is to say that a well with double the initial rate will not achieve double the ultimate recovery. This reinforces the need to create the performance bins; without them we would create a single type curve resulting in an average decline rate. Scaling this average type curve results in moving the curve parallel up and down, thus overestimating the good wells and underestimating the poor wells. Scaling the average well to account for initial decline rates without any frame of reference to how much the decline rate should vary by will also lead to erroneous results.

Tier	*Qi (bbl/d)*	*Di (eff sec)*	*EUR (Mbbl)*
1	70	78.5	45
2	110	83.5	55
3	150	86	65
4	190	86	85
5	230	86	105
6	340	88.5	130
7	450	89.5	155
8	600	91	180

Figure 21 - Initial decline rates increase with increasing initial production rates

With a large sample of wells exhibiting a lognormal distribution of results, it is expected to see the middle type curves bunched closer together, with the high and low ones spread further out (Figure 22).

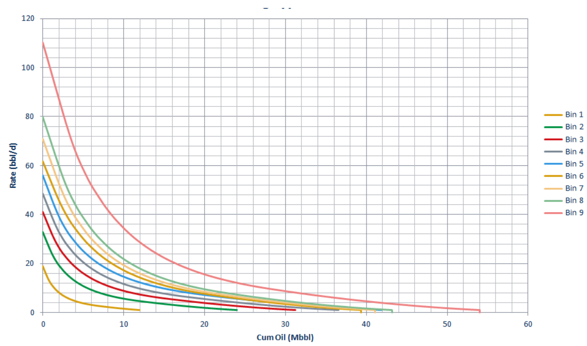


Figure 22 - Creating type curves from the performance bins of a lognormal distribution leads to clumping around the median while data points are spread out at the ends

For this reason, we recommend using the decline parameters, the observed trend of initial decline rates from one type curve to the next and engineering judgment to interpolate between and around the calculated type curves, to create a spectrum of final type curves, or tiers. This spectrum of type curves should cover the entire range of expected results from the play, and can be spaced out as per the preferred methodology of the user (Figure 23). Two possible examples would be to have the tiers spaced out with equal ultimate recovery increments (ie every 25 Mbbls, or 4 m^3), or to have them spaced out with equal percentage increments (ie tier x-1 is 80% of the ultimate recoverable of tier x). Each of these methodologies has its merits, and depending on the intended use one may be more applicable than the other.

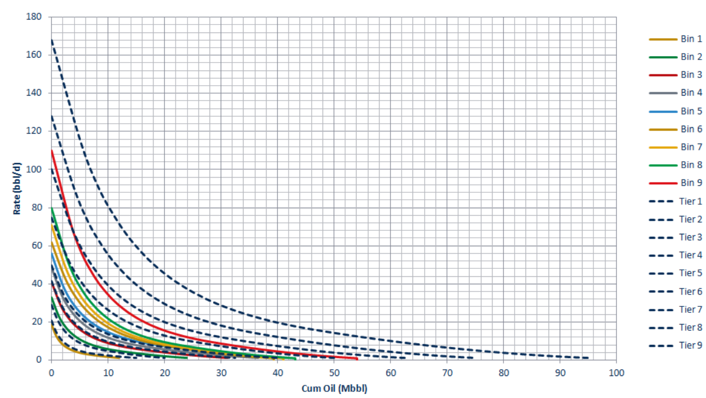


Figure 23 - Type curves created from bins (color) overlain by type curves created by interpolating (dashed)

The workflow is now at the point where a spectrum of type curves has been created covering a range of expected results from the geological bin within the play. This spectrum can now be used to assist in forecasting the production from existing wells, new wells, and future wells.

Applying Typical Performance Curves

The application of the typical performance curves to producing wells is interpretive by nature, much like any production forecasting, and the level of detail that should be applied to the process depends on the end goal and the amount of time and resources available to devote to the process. For example, a reserves evaluation for a year-end reserves certification process would require much more detail and manpower than a simple scoping exercise to determine whether you want to engage in an acquisition process of a company that just opened a data room. We will go through several procedures for applying the type curves, which can be used for different purposes and on wells with different amounts of production history.

The simplest and most efficient manner of applying the type curves parallels the process used to populate all of the wells with forecasts in the type curve creation process. Simply use the average decline exponent and time to boundary dominated flow to populate forecasts to every well, adjusting the initial production rate and decline rate to match the actual production history. The results will not be exact, but for an initial screening process the results will be directionally correct. This methodology does not address any variation in decline exponents from well to well (Figure 24 and Figure 25), nor does it tie the results back to the reservoir geology.

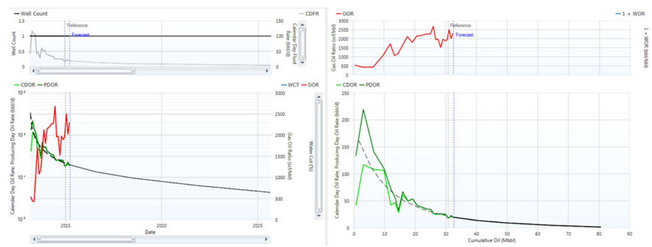


Figure 24 - Example well 1 – actual decline exponent is higher than the average decline exponent that was applied

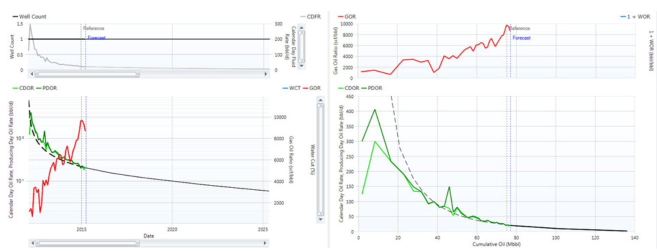


Figure 25 - Example well 2 – actual decline exponent is lower than the average decline exponent that was applied

A more detailed method starts with the same process, but involves more hands on with each well. As each well is populated with a forecast, the decline exponent should also be adjusted to match the actual data (Figure 26 and Figure 27). At the same time, each well could be examined to determine if it is still in linear flow or not, and adjust the time to boundary dominated flow appropriately. When using this method, be careful not to allow personal biases to creep in, where wells only get adjusted upwards but not downwards, or vice versa. This is a very common bias, seen over and over in application of this methodology, and is very difficult to avoid. Having another party review the work, with this bias in mind, can be a very useful tool for avoiding this error.

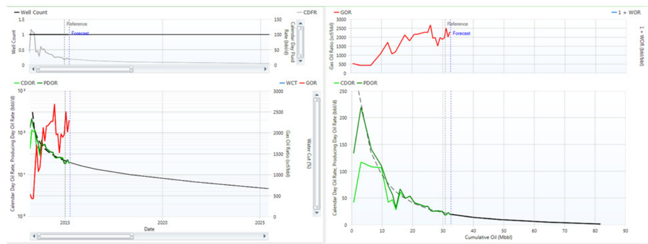


Figure 26 - Example well 1 – decline exponent has been adjusted to match the actual data

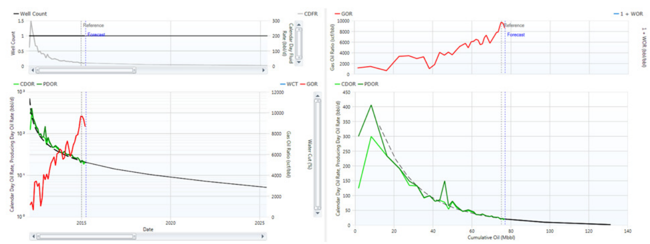


Figure 27 - Example well 2 – decline exponent has been adjusted to match the actual data

Along with this detailed methodology, a review of the forecast recovery factors can provide a high level check for reasonableness. As companies start to drill at higher well densities, we do not necessarily see any difference in production because it takes several years for the production to see no-flow boundaries and start communicating with each other. But with the wells being closer together, we may see steeper decline rates in the boundary dominated flow period or a higher D_{min} than we anticipate, leading our forecasts to be too high in the later years of the life of the well. And added to the rest of the wells in the vicinity, it could lead to a situation where we are forecasting more oil or gas to be recovered than is technically possible or even in place. Checking the forecast recoverable hydrocarbon versus the estimated hydrocarbon in place is recommended for all evaluations. However, it can be done at various levels of detail. It is not necessary to do detailed oil or gas in place calculations for each well and compare the volumes versus the forecast recoverable volumes, but rather a high level check can be used as a screening tool for areas that need further detailed work done. As an example, if we have done enough geological work on the play to know that we have approximately 40 BCF (1.17 e^9m^3) of gas in place per section (640 acres, or 259 hectares), and are developing the reservoir at four wells per section, we have a rough idea of what recoverable volumes per well would start to raise red flags based on our knowledge of what a reasonable recovery factor could be. If there were multiple individual wells in an area forecast to recover 10 BCF (0.28 e^9m^3) per well, and we knew that an upper limit recovery factor of 70% is appropriate for that reservoir, we would want to do more detailed work estimating the gas in place for that area, and consider whether the later years of production forecast should be adjusted in that area.

The more data a well has, the easier it is to predict the future performance of the well. However, new wells can be especially challenging, as the production data does not exist to match the appropriate type curve to. When there is not enough data to back-fit, there are ways of predicting future performance on these wells. Near the beginning of the workflow, we compared various short term key performance indicators with longer term indicators. In this analysis, we saw a general trend that allows us to predict the longer term performance of a well (or more accurately, a group of wells, in aggregate) based on its short term performance. So, given two or three months of production, we can estimate which Tier type curve a well is closest to, and forecast its future production based on that type curve tier. If a well does not have any production data, or any useable production data, then we can predict its performance as if it were an undrilled location.

Assessing Future Development

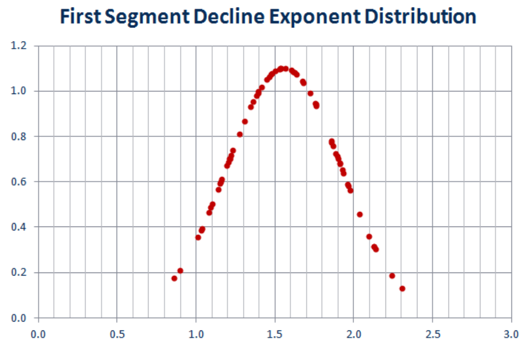
The type curves generated can be applied not only to existing wells, but wells to be drilled in the future as well. Estimating the location of, number of and expected ultimate recovery of undrilled locations is a complex issue, and the guidance of each depends on the application. For example, the rules and guidance surrounding proved undeveloped locations for SEC filings is different than that of proved plus probable undeveloped locations for NI 51-101 or PRMS filings, which are both different from that of contingent or prospective resources under either framework. And different from all of those are a company's procedures for how to value undeveloped acreage in a potential acquisition. Due to the complexity of the issue, procedures and guidance for evaluating undrilled locations is outside the scope of this paper. However, the spectrum of type curves can be applied in all of those situations as a part of the toolkit used to estimate the undrilled potential. Having a spectrum of curves for different reservoir performance within a geologically analogous area allows for improving completion techniques to be captured, and varying levels of performance.

Case Study – Viking Formation in Saskatchewan, Canada

The Viking Formation is located in Townships 23 to 34, Ranges 13 to 28 W3M in west-central Saskatchewan, Canada. The Cretaceous Viking Formation trends northwesterly through eastern Alberta and much of southwestern Saskatchewan. It consists of interbedded sandstones and shales, which were deposited in a shallow epicontinental sea. Eastward into Saskatchewan, the Viking and equivalent strata become thinner and shalier. In the greater Dodsland area of Saskatchewan, a majority of the reservoir rock within the Viking Formation consists of interbedded shaly sandstone and siltstone.

Using the method outlined in this paper, a spectrum of type curves were developed based on wells with production up to June 2014. There were about 3000 horizontal wells drilled into the play at that point in time, with the first wells having been drilled in 2008, 6 years prior. The majority of wells in the sample were drilled over the most recent couple of years though, with the drilling and completions techniques evolving throughout the history of the development of the play.

A random selection of wells was selected to perform the flow regime diagnostics, while ensuring there was representation from all across the play. Wells with too little data, scattered data, or rate restrictions were excluded from the sample, leaving approximately 200 wells. The decline exponents calculated displayed a lognormal distribution with a low P10/P90 ratio, and an average value of 1.7 (Figure 28 and Figure 29).



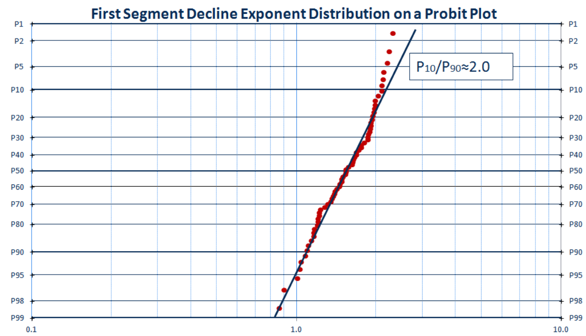
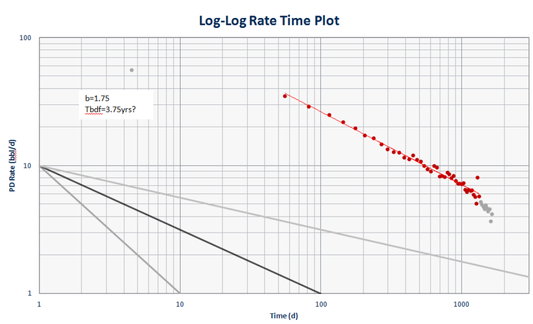


Figure 28 – Lognormal distribution of linear flow decline exponent, mean b=1.7

Figure 29 – Lognormal distribution of linear flow decline exponent shown on probit plot. P10/P90 ratio = 2.0

Investigating some of the wells individually, several wells were observed to be producing for over five years without any sign of boundary effects, while others were observed to show apparent boundary conditions after a bit less than four years of production (Figure 30 and Figure 31). Based on the wells analyzed, a best estimate average time to boundary flow was estimated at approximately four years.



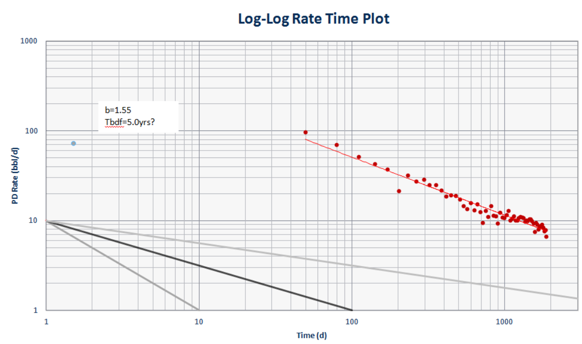


Figure 30 – Well showing linear flow period b=1.75 for approximately 3.75 years, before possibly showing boundary effects

Figure 31 – Well showing linear flow period b=1.55 for over 5 years with no apparent boundary effects

To create performance bins, short term key performance indicators were plotted against longer term performance indicators. It was determined that the 90 day initial rate (3 Mo. IP) was the best indicator of long term performance (Figure 32).

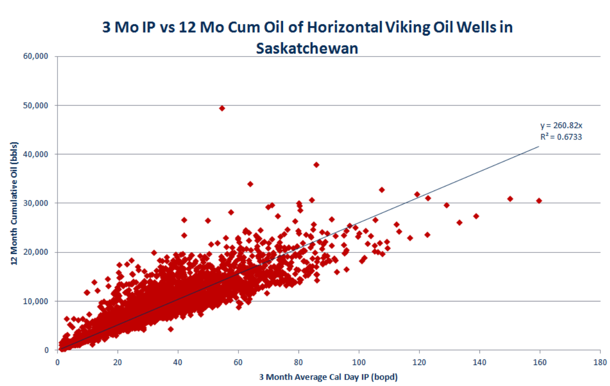


Figure 32 – 3 Month initial rate versus 12 month cumulative production yielded the best fit relationship between performance indicators

Type curves were made for each of the performance bins, and then interpolated to fit the specific needs of the evaluator per company policy (Figure 33).

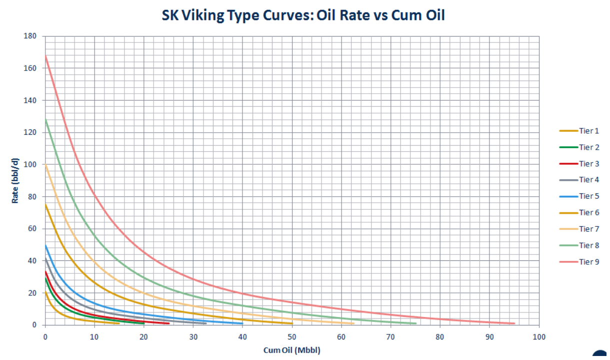


Figure 33 – Resultant type curve tiers

The spectrum of type curves were used to apply forecasts to a selection of wells, which spanned a range of year on date, completion technique, and operator. Some of the wells had as little as 6 months of production, while others had several years of history. Some appeared to have unrestricted production rates, while others showed signs of some restriction. Well by well, some forecasts appear to fit very well (Figure 34).

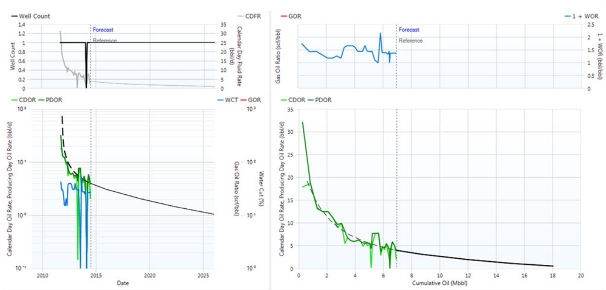


Figure 34 – Example well 3 showing very good back-fit of data

Other wells have limited history and are very difficult to back-fit (Figure 35). The forecasts here rely heavily on the type curves.

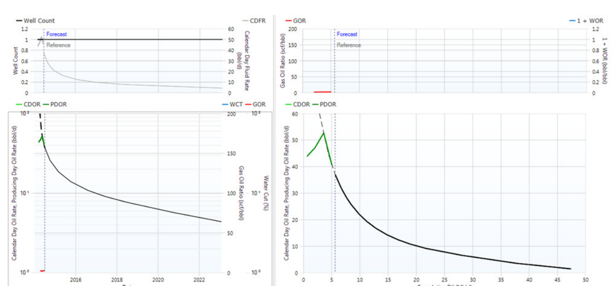


Figure 35 - Example well 4 with very little production history to match

Wells that were rate restricted relied on key performance indicators to pick the appropriate tier to forecast the well with (Figure 36).

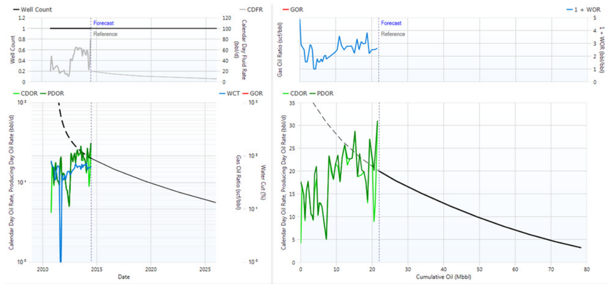


Figure 36 - Example well 5 with a rate restricted production history

But overall, the wells rolled up to an overall summary forecast, predicting the group of wells as a whole (Figure 37).

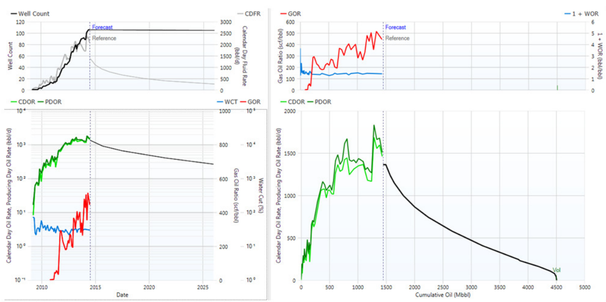


Figure 37 - Rollup of production forecasts from over 100 wells

In order to test how well the process worked, these wells were looked at again after 2 more years of production data were available. Production data was updated on the individual wells, without making any adjustments to the forecasts that were made previously. As expected, some wells production was higher than the forecast rates, while others were lower than the forecast rates. Comparisons are shown for the same wells above in Figure 38, Figure 39 and Figure 40.

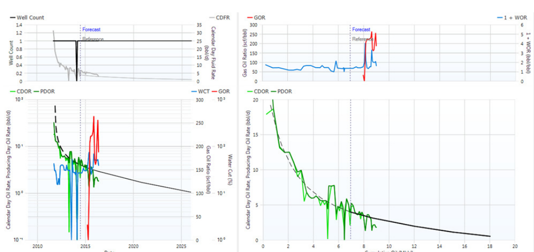


Figure 38 - Example well 3, actual production matched the forecast rates for about a year and a half, then dropped below for the past 6 months

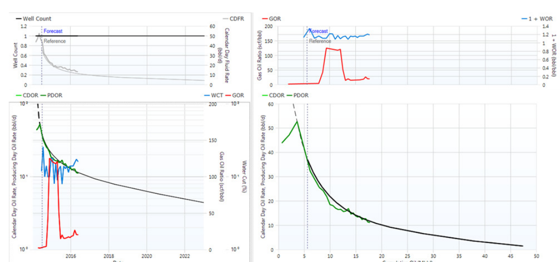


Figure 39 - Example well 4, actual production came in very close to forecast even though there was very little data to forecast off initially

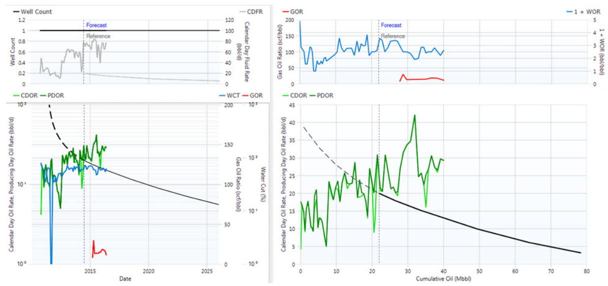


Figure 40 - Example well 5, actual production significantly exceeded forecasts rates. Well continued to produce at restricted rates

The overall production forecast can be compared in the same manner, by rolling up all of the wells with updated production data and unadjusted forecasts (Figure 41).

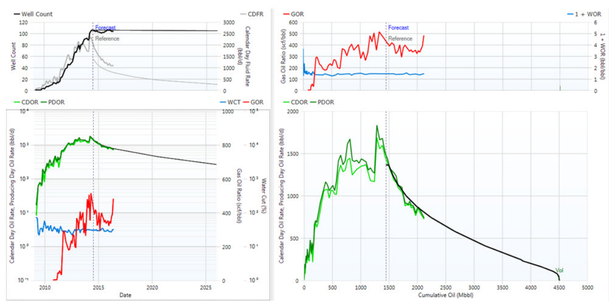


Figure 41 - Actual production overlying the rollup of production forecasts from 2 years prior.

Overall, the forecast rate was very close to the actual rate, with only a 2 percent deviation. Updating the forecasts two years later, individual forecasts would need to be adjusted but the overall forecast would see very little change. Wells with steady producing conditions and wells with little production history typically produced close to the forecast rates, while the wells that were rate restricted tended to be further off. Overall, the workflow performed very well, providing an accurate production forecast for the field.

Case Study – Montney Formation in Alberta, Canada

The Montney Formation was deposited in the Early-to-Middle Triassic Period in environments ranging from inner-continental shelf to deepwater outer shelf. During this time, the paleo-shoreline was oriented northwest-southeast through western Alberta and northeastern British Columbia, Canada. The rock package consists of aeolian-sourced and marine deposits. The source of the aeolian sediments was dune sands of a desert environment, which were transported from the east, from present day Alberta, by wind and deposited on the continental shelf. The coarser sediments were deposited near the shoreline, while the finer sediments were carried further into the sea. In addition to these quartz-dominant deposits, mud and organic-rich materials were also deposited during early Triassic time. The amounts of these materials increased with depth. Thus, the sediments which were deposited further from the shoreline have less clastic material and are muddier. Organic material within the mud is one of the sources of the hydrocarbons in the Montney Formation.

The Montney Formation is typically sub-divided into upper and lower units. The Lower Montney consists of dark grey shales and dolomitic siltstones, while the Upper Montney consists of brownish siltstones and thinly interbedded fine-grained siltstones and coquina.

Turbidite deposits are often found within the Lower Montney Formation. The turbidites occurred when the clastic sediments slid off the continental shelf and flowed far offshore. In such cases, relatively coarse-grained sediments, compared to those of the aeolian-sourced deposits, were carried into deeper water. These turbidite flows create areas of enhanced reservoir properties and can be considered permeability fairways within the Lower Montney. Further away from the paleo-shelf where the sediments are finer-grained, numerous turbidite deposits can inter-finger into the deep water sediments and form high quality reservoirs.

In general, the siltstones and interbedded shales of the Upper Montney Formation are considered higher quality reservoirs in comparison to the Lower Montney Formation.

This case study focused on the Town area within the Montney play, which focuses on developing the Upper Montney. There were about 110 horizontal wells drilled into that portion of the play at that point in time, with the first wells having been drilled in 2009, five years prior. However, half of the wells were drilled in the most recent two years. Like the Viking, the drilling and completions techniques evolved throughout the history of the development of the play. Well had production available up to April 2014 at the time of analysis.

All of the wells were considered for the flow regime diagnostics, but due to rate restrictions or scattered data, half of them were not able to be analyzed. A total of 52 wells were included in the flow regime diagnostics, from which the decline exponents calculated displayed a lognormal distribution with a low P10/P90 ratio, and an average value of around 2.0 (Figure 42 and Figure 43).

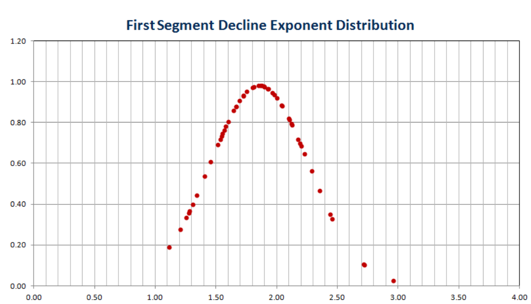


Figure 42 - Lognormal distribution of linear flow decline exponent, mean b=2.0

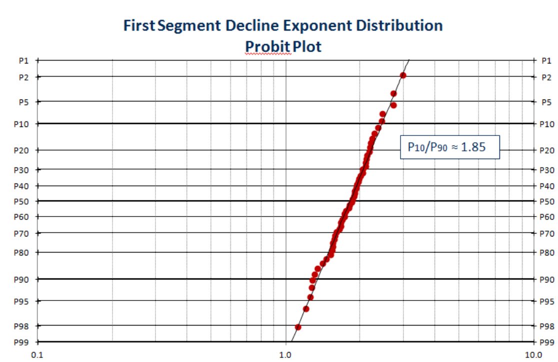


Figure 43 - Lognormal distribution of linear flow decline exponent shown on probit plot. P10/P90 ratio = 1.85

Investigating some of the wells individually, several wells were observed to be producing for over four years without any sign of boundary effects, with only a handful of wells that showed signs of what may be boundary effects, or may only be some scattered data at the end of the dataset (Figure 44 and Figure 45). Based on the wells analyzed, a best estimate average time to boundary flow was estimated at approximately four years.

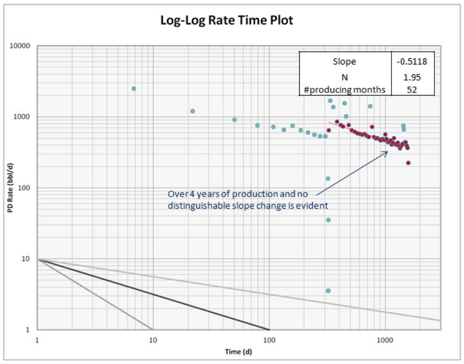


Figure 44 - Well showing linear flow period b=1.95 for approximately 4.3 years, with no sign of any boundary effects

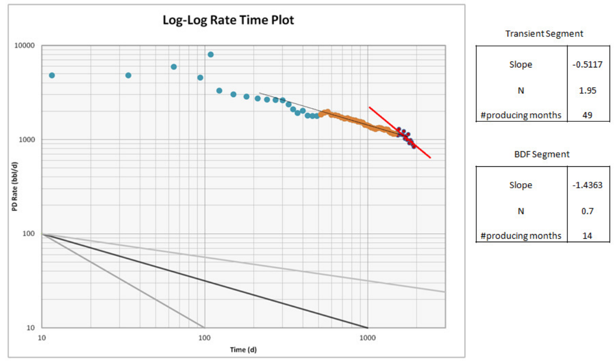


Figure 45 - Well showing linear flow period b=1.9, with a possible boundary effect after 4 years of production,

To create performance bins, short term key performance indicators were plotted against longer term performance indicators. It was determined that the 90 day initial rate (3 Mo. IP) was the best indicator of long term performance, although still fairly scattered (Figure 46).

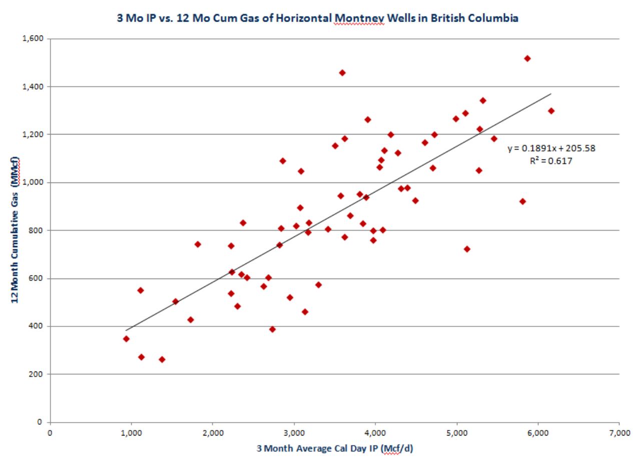


Figure 46 - 3 Month initial rate versus 12 month cumulative production yielded the best fit relationship between performance indicators

Type curves were made for each of the performance bins, and then interpolated to fit the specific needs of the evaluator per company policy (Figure 47).

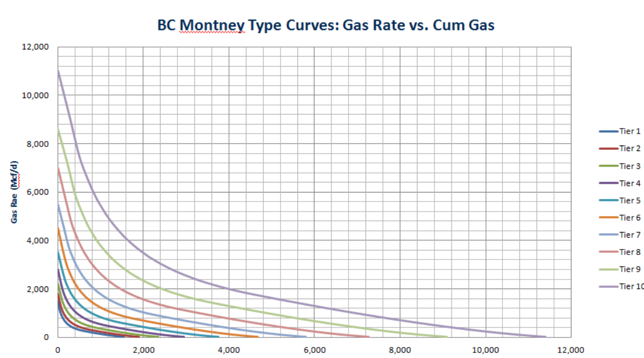


Figure 47 - Resultant type curve tiers

The resulting type curves were used to apply forecasts to all of the 109 wells. Some of the wells had as little as 6 months of production, while others had several years of history. Most of the wells were drilled within the prior two years. Some appeared to have unrestricted production rates, while others showed signs of some restriction. Well by well, some forecasts appear to fit very well (Figure 48).

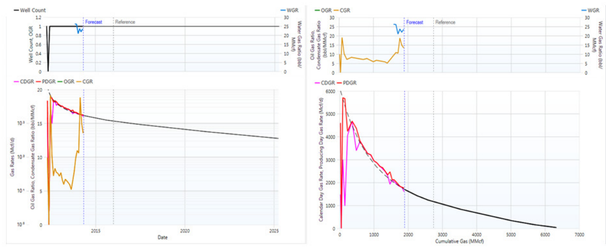


Figure 48 – Example well 6 showing very good back-fit of data

Other wells have limited history and are very difficult to back-fit (Figure 49). The forecasts here rely heavily on the type curves.

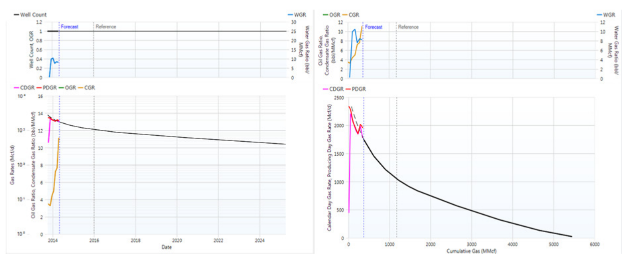


Figure 49 - Example well 7 with very little production history to match

Wells that were rate restricted relied on KPIs to pick the appropriate tier to forecast the well with (Figure 50).

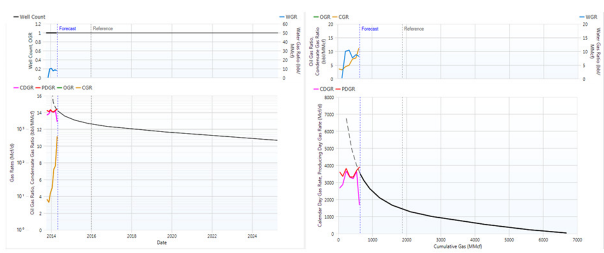


Figure 50 - Example well 8 with a rate restricted production history

But overall, the wells rolled up to an overall summary forecast, predicting the group of wells as a whole (Figure 51).

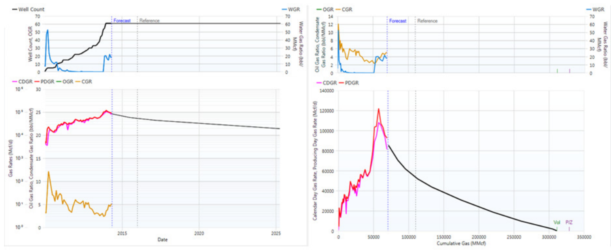


Figure 51 - Rollup of production forecasts from all 109 wells

Similar to the Viking case study, these wells were looked at again after 2 more years of production data were available. Again, production data was updated on the individual wells, without making any adjustments to the forecasts that were made previously. Some wells production was higher than the forecast rates, while others were lower than the forecast rates. Comparisons are shown for the same wells above in Figure 52, Figure 53 and Figure 54.

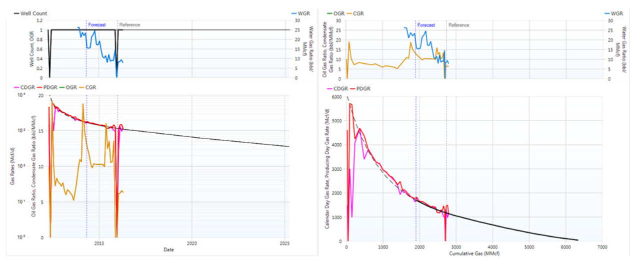


Figure 52 - Example well 6, actual production matched the forecast rates very accurately

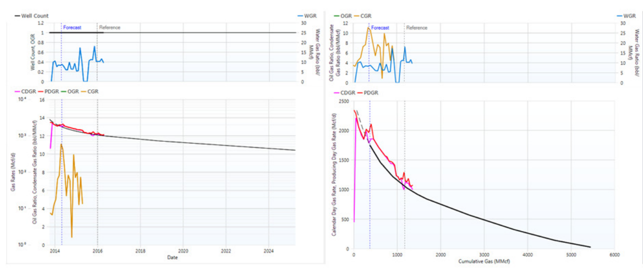


Figure 53 - Example well 7, actual production came in a bit higher than forecast, although pretty close.

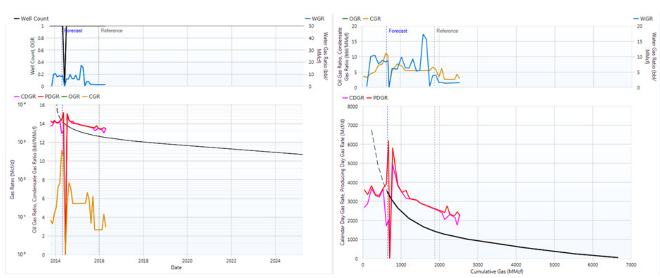


Figure 54 - Example well 8, actual production exceeded forecasts rates by quite a bit. Well continued to produce at restricted rates for a short time before declining

The overall production forecast can be compared in the same manner, by rolling up all of the wells with updated production data and unadjusted forecasts (Figure 55).

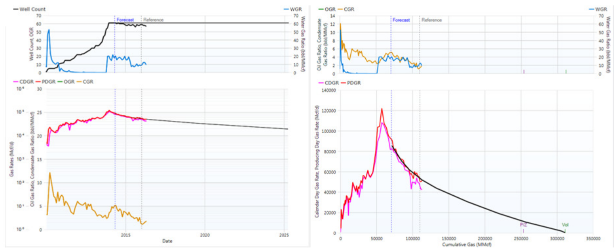


Figure 55 - Actual production overlying the rollup of production forecasts from 2 years prior

Overall, the forecast rate was very close to the actual producing day rate, again only a couple percent off. The forecast rate was a bit higher than the calendar day rate though, as there were some disruptions in the area causing downtime over the past year. Like with the Viking, individual wells needed to be adjusted when updating the forecasts with two more years of production, but overall the rolled up forecast would see very little change. Wells with steady producing conditions and wells with little production history typically produced close to the forecast rates, while the wells that were rate restricted tended to be further off. Again, the workflow proved to be successful in providing an accurate production forecast in aggregate, this time with fewer wells to analyze, and less production history to work with.

Conclusions

The oil and gas industry has made a lot of progress in understanding the fundamentals of fluid flow and reservoir dynamics in fracture stimulated low permeability reserves over the past number of years, a lot of which was brought together in Monograph 4. This technical work needs to continue, and is a fundamental aspect of our industry. This workflow has pulled these fundamentals together in a process that allows large numbers of wells to be evaluated in an efficient manner, yielding results that can be relied upon by technical teams, managers, or executive to make the decisions necessary to run their company. The workflow has evolved over the past two years, and will continue to evolve as we gain a fuller understanding of low permeability reservoirs and commercial software packages build more of the workflow into their programs. The workflow has been designed to be software agnostic, allowing companies to tailor specific points to meet their individual needs and work with their individual resources. However, the more steps that are built into commercial software packages, and not done manually, the more efficient the process will be. The workflow allows wells with different completion techniques to be analyzed together, making the analysis more robust and maximizing the statistical significance by not breaking the sample up into smaller groups. Creating a spectrum of tiers as the end results allows the user to know what each level of performance looks like, and be able to predict how a group of wells with superior completions will act. Utilizing a process that increases efficiency in this manner allows companies to focus more on their technical or economic analysis, rather than spending a time tediously forecasting production for many wells.

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