An Integrated Technique for Production Data Analysis (PDA) With Application to Mature Fields

R. Gaskari, S.D. Mohaghegh and J. Jalali, West Virginia University

Summary
The most common data that engineers can count on, especially in mature fields, is production rate data. Practical methods for production data analysis (PDA) have come a long way since their introduction several decades ago and fall into two categories: decline curve analysis (DCA) and type curve matching (TCM). DCA is independent of any reservoir characteristics, and TCM is a subjective procedure.

State of the art in PDA can provide reasonable reservoir characteristics, but it has two shortcomings: First, for reservoir characterization, the process requires bottomhole or wellhead pressure data in addition to rate data. Bottomhole or wellhead pressure data are not usually available in most of the mature fields. Second, a technique that would allow the integration of results from hundreds of individual wells into a cohesive fieldwide or reservoir-wide analysis for business decision making is not part of today’s PDA tool kit.

To overcome these shortcomings, a new methodology is introduced in this paper that has three unique specifications:
- It does not “require” pressure data, bottomhole or wellhead (but it can make use of it, if available, to enhance accuracy of results).
- It integrates DCA, TCM, and numerical reservoir simulation or history matching (HM) to iteratively converge to a near unique set of reservoir characteristics for each well.
- It uses fuzzy pattern recognition technology to achieve fieldwide decisions from the findings of the analysis.

Introduction
Techniques for PDA have improved significantly over the past several years. These techniques are used to provide information on reservoir permeability, fracture length, fracture conductivity, well drainage area, original gas in place (OGIP), estimated ultimate recovery (EUR), and skin. Although several methods are available to characterize the reservoir, there is not a unified method that always yields the most reliable answer.

DCA is a method to fit observed production rates of individual wells, group of wells, or reservoirs by a mathematical function to predict the performance of the future production by extrapolating the fitted decline function.

Arps (1945) introduced the DCA method in the 1940s. The method is a mathematical equation with no physical basis other than the equation that shows a declining trend. Arps’ method is still being used because of its simplicity. In the early 1980s, Fetkovich (1985) introduced DCA by type curves. Fetkovich used Arps’ decline curves along with type curves for transient radial symmetric flow of low-compressibility liquids at constant bottomhole pressures. Fetkovich related Arps’ decline parameters to some reservoir engineering parameters for production against constant bottomhole pressures. Several other type curves have been developed by Carter (1985), Fraim & Wattenbarger (1987), Palacio & Blasingame (1993) and Agarwal et al. (1999) and others for different well and reservoir conditions.

Several commercial PDA tools have been developed for the oil and gas industry. These commercial applications use DCA, TCM, and/or HM (using reservoir simulation) independent from each other without integrating these techniques. Furthermore, no other technique that is currently in use provides facilities to integrate the results from individual well analysis into a fieldwide (reservoirwide) analysis.

Methodology
The new technique discussed in this article is called intelligent production data analysis (IPDA). The physics and the mathematical models behind the technique are the same as those used in DCA, TCM and HM using a numerical simulator. Since none of these techniques are new and all have been well documented, the reader is referred to some references for a deeper look into these methods. The contribution of the technique introduced in this article is two-fold: First, it is the iterative integration of the three (previously mentioned) techniques on a well-to-well basis (Fig. 1), and second contribution is the use of fuzzy pattern recognition to expand the analysis from a single well into an entire reservoir (field). In this way, a complete analysis of a single well becomes a small part that contributes to a larger integrated analysis encompassing the entire field or reservoir.

The following is a brief overview of the procedures involved in this technique.
- **DCA:** DCA is used as a temporary benchmark for estimating $b$ and EUR. It is a widely known fact that DCA is a mathematical technique of forecasting well performance with no physical basis.
- **TCM:** TCM is performed using a set of type curves that are generated based on the $b$ value (hyperbolic exponent) that was obtained from DCA. This essentially ties the two techniques together. Using this unique $b$ value to generate the type curves reduces the subjectivity in the TCM (TCM) process.

Some parameters such as the initial reservoir pressure and bottomhole pressure used in TCM could be guessed with reasonable accuracy for a reservoir. Since this method incorporates an iterative process, the assumed values for the initial reservoir pressure and the well bottomhole pressure are modified to obtain a reasonable match.
- **HM:** In HM, the results of TCM (i.e., drainage area, fracture half-length, and permeability as well as parameters that were assumed for their calculation such as pay thickness, porosity, gas saturation, and initial and bottomhole pressure) are used as the starting point. Since HM provides nonunique solutions, use of the previously mentioned parameters as a starting point provides a better and quicker convergence with a higher probability for a better match. Furthermore, the EUR from DCA and TCM is used as another controlling point for HM convergence.
- **Intelligent, Iterative, and Integration.** These three techniques are integrated through an iterative process that eventually converges to provide a set of representative reservoir characteristics.
- **Fuzzy Pattern Recognition.** Upon completion of the above analysis for every well in the field, the results [reservoir characteristics as well as production indicators (PI)] are integrated to determine and deduce specific patterns in the field. Recognition of such patterns can point to sweet spots, underperforming wells, and remaining reserves, among other important reservoir information.

The process begins by plotting production rate and cumulative production vs. time on a semilog scale. An automatic optimization routine based on genetic algorithms identifies the best decline curve for the given well, as both the rate vs. time and the cumulative production vs. time are simultaneously matched. This is
demonstrated in Fig. 2 for a well in the Wattenberg field producing from Codell and Niobrara formations in the D.J. Basin of Rockies. Initial production rate $Q_i$, initial decline rate $D_i$, and hyperbolic exponent $b$ are automatically identified. Additionally, the 30-year EUR is calculated. The information that results from the DCA is then passed to a TCM procedure. The appropriate type curves for the reservoir and fluid that is being investigated are selected. For the purposes of this article, the type curves developed by Cox et al. (1995) (or low-permeability gas reservoirs assuming constant bottomhole pressure) were used, since gas production from tight gas sands were being investigated.

Fig. 3 shows the production data from the well pictured in Fig. 2. The actual production is plotted on a log-log scale on top of a series of type curves, which are developed for the same value of hyperbolic exponent that was found during the DCA. Fig. 3a illustrates similar production data plotted on a set of type curves for a different hyperbolic exponent. The production data plotted in Figs. 3a (top) and 3b (bottom) shows that the data can be matched with any of the curves. This demonstrates the subjectivity of TCM.

If the results of the DCA are satisfactory, (note that the match achieved in the DCA is subject to iterative modification and can be improved—the initial match is only a starting point), there is no reason to not take advantage of the results of the DCA to increase the likelihood of success and eliminate the subjectivity of the TCM.

In Fig. 4, we have taken full advantage of the results of DCA. This has been accomplished by plotting the production data resulting from DCA rather than the actual production data and by using the 30-year EUR calculated from the DCA for this well [i.e., 285.75 MMscf (Fig. 2)], as a guide to move data up and down to match it on different $X_e/X_i$ curves until a calculated 30-year EUR is achieved that is reasonably close to that of DCA. For this particular well, as shown in Fig. 4, the EUR is 286.5 MMscf.

Upon completion of TCM procedure, permeability, fracture half-length, and drainage area are calculated. If during TCM within the iterative process a good match cannot be achieved (a good match is defined as a match that appears reasonable during visual inspection but also provides logical values for the parameters while the EUR is relatively close to that of the DCA), we must return to the DCA and modify the match there to achieve a different $b$ and EUR and then repeat the TCM. Experience with this procedure has shown that most frequently a single iteration provides acceptable results.

Knowledge about a set of parameters for the reservoir (or field) being studied is necessary to complete the TCM process. These parameters are used to calculate permeability, fracture half length, drainage area, and EUR. These parameters include initial reservoir pressure; average reservoir temperature; gas specific gravity; isotropicity ($k_x/k_z$ ratio); drainage shape factor ($L/W$ ratio); average porosity; average pay thickness; average gas saturation; and average flowing bottomhole pressure. Most of these parameters can be (and usually are) estimated within an acceptable range for a particular field. By having access to well logs from some (or all) of the wells, porosity, thickness, and gas saturation for each well can be calculated and used during the analysis.

The third and final step of the first component of IPDA is numerical reservoir simulation. The reservoir simulation step itself is divided into two parts. First is the HM, and second is Monte Carlo simulation. During HM, all of the accumulated information from the DCA and TCM is used to initialize a single-well, radial numerical simulator. To achieve an acceptable match, the accumulated information from the DCA and TCM will be modified. If the modifications to any of these parameters prove to be significant, then the user must return to the prior techniques, modifying...
them in the direction that shows the most reduction in the magnitude of the modifications in the HM process. If the modifications prove to be insignificant, then we can move to the next step.

After a HM has been achieved, a probability distribution function (PDF) is given to any crucial parameters that are part of the simulation process, and the objective function (which is the history matched model) is run 500 to 1,000 times. Number of iterations identifies the number of times for each of the PDFs to be sampled and the simulation to be executed.

Each time a run is completed, the 30-year EUR is calculated, and at the end, they are plotted to form a 30-year EUR PDF. The calculated 30-year EUR from DCA and TCM is marked on the 30-year EUR PDF plot. As long as the 30-year EUR calculated from the DCA and TCM is within the high-frequency area of the plot, then the results of the analysis are acceptable. Fig. 5 shows the result of a Monte Carlo simulation for the well with the HM shown in Fig. 6.

Once the individual analysis for all of the wells in the field is completed, the following information for all the wells in the field is available: initial flow rate \( q_i \), initial decline rate \( D_i \), hyperbolic exponent \( b \), permeability \( k \), drainage area \( A \), fracture half length \( X_f \), and 30 Year EUR.

Fig. 3—TCM with real production data is a subjective process.
The second part of the analysis (fuzzy pattern recognition) is intended to integrate the above information in the context of the entire field to illustrate the field’s present status and to predict the field’s status at any time in the future. On the basis of the predictions of changes that the field (or reservoir) may undergo in the future, this part of the analysis permits engineers and managers to make business and engineering decisions that will maximize return on investments.

PIs are calculated for each well on the basis of the rate vs. time data. These PIs offer a measure of each well’s production capability, which can be used for comparison with the offset wells. The PIs that are automatically calculated for each well at the start of this procedure are the best 3, 6, 9, and 12 months of production; the first 3, 6, 9, and 12 months of production; 3, 5, and 10 years cumulative production; and current cumulative production.

DCA results are used to calculate remaining reserves for each well. Remaining reserves are calculated based on EUR from which the cumulative production has been subtracted. IPDA deduces and generates 2D and 3D patterns and maps over the entire field (using...
Results and Discussions

The methodology described in this paper was applied to production data from 137 wells in the Wattenberg field producing from Codell and Niobrara formations in the D.J. basin of the Rocky Mountains. Monthly production rate data were the only data used to perform this analysis. The first step in the process is integrating DCA, TCM, and numerical reservoir simulation (or HM) to converge to a near-unique set of reservoir characteristics for each well. Fig. 7 shows the results of all three analyses for one of the wells in the field. From top to the bottom, the graphs are DCA, TCM, HM, and Monte Carlo simulation, respectively.

Figs. 8 and 9 show 2D maps of the wells in the Wattenberg field. The maps include 137 wells. In Fig. 8, the field has been partitioned on the basis of first 3 months of production, and Fig. 9 shows the field when partitioned on the basis of the first 3 years of production.

The relative reservoir quality index (RQI) is shown for each region with a number from 1 to 5 in both figures. A lower RQI means higher reservoir quality. For example, Fig. 8 shows an average well in RQI = 1 produces about 61 MMscf, while an average well in RQI = 5 produces about 10 MMscf during the first 3 months of production. The first 3 months of production for an average well in RQI of 2 and 3 in this field is 36 and 22 MMscf, respectively.

Comparing Figs. 8 and 9 shows that as time passes, the size of the partitions changes. Although all the partitions are relative (as the name suggests), more-productive partitions decrease in size as some wells change from higher productivity partitions to lower-productivity partitions. For example, the two wells in the top of partition 3 during the first 3 months of production (see Fig. 8) move to a less productive partition (RQI = 4) during the partitioning of the first 3 years of production (Fig. 10). The two wells in the left side of partition 1 behave similarly (see Fig. 8). These wells move to partitions with RQI of 2 in Fig. 9.

Movement of these wells from one partition to another may indicate relative reservoir depletion. Fig. 10 shows the partitioning of the reservoir based on the last month’s production of each well. Comparing the fuzzy pattern recognition curves along with the latitude and the longitude, one may note significant changes between Figs. 8 and 9 when compared to that of Fig. 10. It is also obvious in the partitioning that the sweet spot (partition with RQI = 1) has moved to the southern side of the field. It is also notable that the most productive part of the field has an average production that is more than 6 times that of the least productive parts of the field. Fig. 10 shows that an average well in the most productive section of the field produces about 8.6 MMscf/month, while an average well in the least productive areas of the field would produce about 1.4 MMscf/month. A simple averaging of production rates does not provide such information.

One of the parameters calculated during this process was the drainage area, and Fig. 11 shows fuzzy pattern recognition applied to the drainage area. Better wells located in the southern part of the field drain as much as 18 acres while the least productive wells, mainly in the northeastern part of the field, have an average drainage area of about 4 acres.

In Fig. 12, the 3D view shows the drainage area, fracture half-length, and permeability patterns in the Wattenberg field producing from Codell and Niobrara formations in the D.J. basin because of production from the 137 wells over the past several years. Please note that there are far more wells producing in this field than have been analyzed in this article. The purpose here was to demonstrate the application of this technique to wells in the D.J. basin.

Patterns show the locations that have higher permeability values and that appear to lie along the midsection of the field, especially in the center. The drainage area shows larger values toward the southern part of the field, especially on the western side. The fracture half-length shows larger values in the midsection of the field, especially in the center.

Managers, geologists, and engineers are able to develop strategies for further developing this field with the use of such views of the formation. Using the concept demonstrated in Fig. 7, the remaining reserves in this field are mapped and are shown in Fig. 13. The remaining reserves are plotted as a function of time, assuming no new wells are drilled.

Fig. 6—Results of Monte Carlo simulation with EUR as the objective function performed on the same well as in Fig. 8.
Fig. 13 illustrates projected depletion in the reservoir from 1998 to 2090, showing portions of the field that would have remaining reserves that could be developed. The infill wells need to be strategically placed where they would contribute to an efficient depletion of the reservoir.

Validation of IPDA

Just as any new technique that is introduced, IPDA must prove itself through a rigorous validation process. Since the objective of IPDA is to perform qualitative reservoir characterization, recommend new drilling locations, and predict well performance, then it would be reasonable to expect that it would do so with reasonable accuracy if the date of the analysis is pushed back. This means that if instead of 2006 the analysis were performed in 1996, then IPDA should be able to predict the performance of the wells drilled since 1996 with reasonable accuracy.

To demonstrate IPDA’s forecasting capabilities the 137 wells in the field were divided into two sets. The first set included 105 wells (77% of all wells being analyzed) that have been producing since 1984, with the latest drilling date of 1993. The remaining 32 wells (23% of the wells being analyzed) had been drilled starting in 1994 and later. The analysis that was mentioned in this article was performed on the first set of wells (77% of the wells that had been drilled and had been producing prior to 1993). The results of the analysis were used to predict the performance and characteristics of the wells that were drilled since 1994. Monthly production

Fig. 7—Results of all three techniques for one of the wells in the Wattenberg field producing from Codell and Niobrara formations in the D.J. basin.
information of the 32 wells was available and used for validation of the technique.

In Fig. 14, fuzzy pattern recognition is performed on the 105 wells drilled and produced before 1994. These wells are shown as white circles. The blue circles indicate the 32 wells that were drilled after 1994. Of the 32 wells, 3 fall outside of the regions that IPDA can make any predictions. The other 29 wells fall. Regions 1 through 6 and, therefore, can be analyzed. In the above figure, Regions 1, 3, and 5 have been classified as RRQI B, Region 4 is classified as RRQI A and Regions 2 and 6 are classified as RRQI C. Table 1 shows the minimum and maximum values of the first 3 months of production for each of the regions and RRQIs.

Fig. 15 shows the average value of the first 3 months of production for new wells drilled in each region as compared to the minimum and maximum value of each region. This figure shows that in all cases (excluding Region 6), the average value of the PI (or the first 3 months of production) falls within the minimum and maximum of the region. This exercise is repeated for another PI, the cumulative production after the first year. Fig. 16 shows the average value of first year of production for new wells drilled in each region as compared to the minimum and maximum value of each region. This figure also shows that in all cases (excluding Region 6), the average value of the PI falls within the minimum and maximum of the region. In both cases, the prediction in Region 6 falls short of expectation. This region includes two new wells out of the 29 (approximately 7%) that are analyzed that do not pass the validation test. To further validate the technique, this time, instead of a measured value such as first 3 months or first
<table>
<thead>
<tr>
<th>Well No</th>
<th>Production (MMscf)</th>
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<tbody>
<tr>
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<td>1 (61 MMscf)</td>
</tr>
<tr>
<td>2</td>
<td>2 (36 MMscf)</td>
</tr>
<tr>
<td>3</td>
<td>3 (22 MMscf)</td>
</tr>
<tr>
<td>4</td>
<td>4 (16 MMscf)</td>
</tr>
<tr>
<td>5</td>
<td>5 (10 MMscf)</td>
</tr>
</tbody>
</table>

**Fig. 8**—RRQI based on first 3 months of production.

<table>
<thead>
<tr>
<th>Well No</th>
<th>Production (MMscf)</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>1 (239 MMscf)</td>
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<tr>
<td>2</td>
<td>2 (151 MMscf)</td>
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<tr>
<td>3</td>
<td>3 (117 MMscf)</td>
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<tr>
<td>4</td>
<td>4 (72 MMscf)</td>
</tr>
<tr>
<td>5</td>
<td>5 (67 MMscf)</td>
</tr>
</tbody>
</table>

**Fig. 9**—RRQI on the basis of the first 3 years of production.
Fig. 10—RRQI on the basis of the last month of production.

Fig. 11—Partitioning of the reservoir RRQI on the basis of the average drainage area of the wells.
year of production, the validation is repeated with an interpreted parameter such as permeability.

Fig. 17 shows the division of the field into three different reservoir qualities identified as A, B, and C (A being the best quality). Minimum and maximum permeability in each of the 6 regions that are identified in Fig. 18 are shown in Table 2 along with the RRQI.

Fig. 16 shows that like the other, PI average value of permeability (after interpretation using the same technique that was covered in this article) falls within the range of each region. Region 3 is the only region that does not follow the trend, and its average value of permeability for the new wells drilled in this region is below the minimum of the region. This region includes one new well out of the 29 (less than 1%) that are analyzed that do not pass the validation test.

Conclusions
An integrated technique for fieldwide PDA has been introduced in this paper. Intelligent PDA IPDA uses an automated, innovative, and iterative technique that integrates DCA, TCM, and numerical reservoir simulation or HM, merging the data into a set of reservoir characteristics that is compatible with all three techniques.

When all the reservoir characteristics are identified using this process, a unique fuzzy pattern recognition technology is used for all the wells in the field, and the results are mapped on the entire field to estimate the reserves, determine optimum infill drilling locations, follow fluid flow and depletion, verify remaining reserves, and detect underperforming wells.

References


Fig. 13—Average value of the new wells as compared to minimum and maximum of each region, first 3 months of production.

Razi Gaskari, Ph.D. is a research assistant professor of petroleum engineering at West Virginia University. Gaskari’s research areas are mostly related to intelligent systems application, data mining, and geographic information systems in different engineering principals. Gaskari conducted several research projects in the area of artificial intelligence technologies applied to the petroleum industry to solve complex nonlinear problems (i.e., reservoir characterization, workover/stimulations/infill drilling candidate selection, performance prediction, fracture design, and production optimization. He has published more than 19 technical papers during his career and has been a technical reviewer for SPE Reservoir Evaluation and Engineering Journal since 2006. Gaskari holds a BS degree in civil engineering from Sharif University of Technology, Tehran.
Iran and an MS and a PhD degree in environmental engineering from West Virginia University. Shahab D. Mohaghegh is a professor of petroleum engineering at West Virginia University. Mohaghegh is founder and president of Intelligent Solutions, Inc. His research and development efforts in application of artificial intelligence in the oil and gas industry date back to 1991. He has published more than 90 technical papers in this area. Mohaghegh has successfully applied AI techniques to drilling, completion, formation evaluation, reservoir characterization, simulation and reservoir management. Mohaghegh is a technical review chair for the SPE Reservoir Evaluation and Engineering Journal. He has served as discussion leader in many SPE forums and is steering committee member in SPE applied technical workshops. He has been featured four times as a SPE distinguished author in the SPE Journal of Petroleum Technology and is a SPE Distinguished Lecturer (2007–2008). Mohaghegh holds BS and MS degrees in natural gas engineering from Texas A&M University and a PhD in petroleum and natural gas engineering from Penn State University. Jalal Jalali is a graduate research assistant in the petroleum and natural gas engineering department at West Virginia University. Jalali’s research interests are coalbed methane simulation and modeling, CO₂ sequestration MMV, and production data analysis. He is currently focusing on CO₂ sequestration MMV in coal for his PhD dissertation. Jalali graduated from Tehran University Tehran, Iran in 2000 with a BS degree in metallurgical engineering and received his MS degree in petroleum and natural gas engineering from West Virginia University in 2004.

Fig. 14—Average value of the new wells as compared to minimum and maximum of each region, first year of production.

Fig. 15—Fuzzy pattern recognition of existing wells and prediction of validation wells for permeability.
Fig. 16—Average value of the new wells as compared to minimum and maximum of each region, permeability.

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<th>Max., mscf</th>
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</tr>
<tr>
<td>3</td>
<td>B</td>
<td>24,581</td>
<td>61,754</td>
</tr>
<tr>
<td>5</td>
<td>B</td>
<td>24,581</td>
<td>61,754</td>
</tr>
<tr>
<td>6</td>
<td>C</td>
<td>19,639</td>
<td>37,351</td>
</tr>
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Fig. 17—3D patterns developed by information calculated through integrated techniques.

<table>
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<th>Max., md</th>
</tr>
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<tbody>
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<tr>
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<tr>
<td>5</td>
<td>B</td>
<td>0.38</td>
<td>0.94</td>
</tr>
<tr>
<td>6</td>
<td>C</td>
<td>0.19</td>
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<tr>
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<td>A</td>
<td>0.94</td>
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Fig. 18—Evolution of remaining reserve through time in the D.J. basin.