Listening to the Reservoir—Interpreting Data From Permanent Downhole Gauges

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Abstract

The permanent downhole pressure gauge is a class of tool that has become popular in the industry. These tools are installed during the well completion and provide a continuous record of pressure changes during production. Permanent downhole gauges (PDGs) have potential to provide more information than is available with traditional well testing, which is carried out for a relatively short duration. PDGs may provide useful information regarding changes in reservoir properties or well conditions with time as the reservoir is produced.

However, interpretation of PDG data is a new problem. Unlike the traditional well test in which "disturbances" in the reservoir (i.e., rate changes) are created and pressure and rates are both known, the changes in rates associated with the record from the PDG may not be known. Moreover, the dynamic changes in the reservoir, along with changes in the flowing temperature or changes in the gauge itself, make the data more complicated to interpret.

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Introduction

Developing petroleum resources in an optimal manner requires making many complex decisions on the basis of expectations of future reservoir performance. Central to forecasting reservoir performance is creation and calibration of a reservoir model. These interrelated tasks generally are known as reservoir description and history matching. Most data used for history matching are in the form of surface-measured rates and cumulative volumes of production (oil, gas, and water) and injection (water and gas). However, improving both the creation of a reservoir model and its calibration to replicate measured reservoir history requires collecting measurements from the reservoir itself. In many cases, these downhole data include measurements of pressure, flow rate, and temperature as functions of time. Traditionally, such measurements were made with wireline gauges. However, during the past 20 years, the application of permanently installed gauges has become increasingly common. As of 2006, the number of permanently installed gauges is probably in excess of 10,000 worldwide [Chorneyko (2006) quotes more than 1,000 for one major oil company alone]. Advantages of PDGs have been demonstrated in the field, and many authors have reported their cost-effectiveness. Most early PDG installations were used for operational objectives, such as monitoring pumps and downhole equipment. However, it soon was evident that PDGs also were a good source of information about the reservoir itself. This paper focuses on the use of PDGs for reservoir modeling, specifically on innovative technologies required to best use this new data source.

Although PDGs were installed as far back as 1963 (Nestlerode 1963), they were not commonly used until the late 1980s. Increasing sophistication and cost of well completions represented a target for better information about events taking place downhole, in real time. Simultaneously, increased reservoir-characterization sophistication added new requirements for downhole reservoir data. Early in the 1990s, the North Sea became a leader in the use of data from PDGs for reservoir management, as described by Shepherd et al. (1991), Unneland and Haugland (1994), and Unneland et al. (1998). PDG applications have since become common worldwide [see Chorneyko (2006) for examples].

In the reservoir-engineering context, a permanent downhole pressure gauge registers changes in reservoir pressure as a function of changes in well flow rate. As such, from a conceptual viewpoint, the data can be much like those collected in a conventional wireline test, such as a buildup or a drawdown test. In addition to some commonalities, there are some important differences between PDG data and conventional wireline well-test data, both with the data and with the manner of their use.

Data. Considering the nature of the data, changes registered by PDGs are subject to far less control than the changes imposed during a conventional well test. A conventional well test is designed to render the imposed change in the flow rate to be as simple as possible, evoking a simple and easily interpreted pressure response from the reservoir. The unrestrained fluctuations in well condition measured

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by a typical PDG are much more complex in character, and require different analysis tools for interpreting the resulting data.

Use. Considering the manner in which PDGs are used, one of the most defining characteristics is the inherent combination of short- and long-term transients. These transients permit dual application of these data to infer short-term effects (e.g., skin effect) and longer-term effects such as pressure depletion or changes in reservoir mechanism. With respect to the longer-term changes, PDG data are especially useful for history matching.

Reservoir-Engineering Uses of PDG Data

Kragas et al. (2004) listed several examples in which PDG data were used in reservoir monitoring at the Northstar field in Alaska. These applications included the following.

- Reservoir-pressure measurement
- Flowing-bottomhole-pressure management
- Providing data in place of shut-in (buildup) tests
- Skin determination
- Detecting compartmentalization (monitoring interference effects)
- Voidage control
- Tubing-hydraulics matching
- Inflow-performance modeling
- Monitoring of well treatments, such as perforation

In addition, history matching could be added as described by several authors, for example de Oliveira and Kato (2004).

All of these tasks may be achieved by instruments mounted permanently downhole, and thereby avoid the time, expense, and risk associated with wireline intervention. Kragas et al. (2004) estimated in the case of Northstar that the avoidance of wireline buildup testing (i.e., 2-days duration, 6 wells, with 10,000 STB/D of lost production per well) resulted in the acceleration of 120,000 STB for each avoided buildup-test campaign, or a total of 650,000 STB over the life of the field. They also estimated a savings of USD 1.6 million in avoided wireline-service costs.

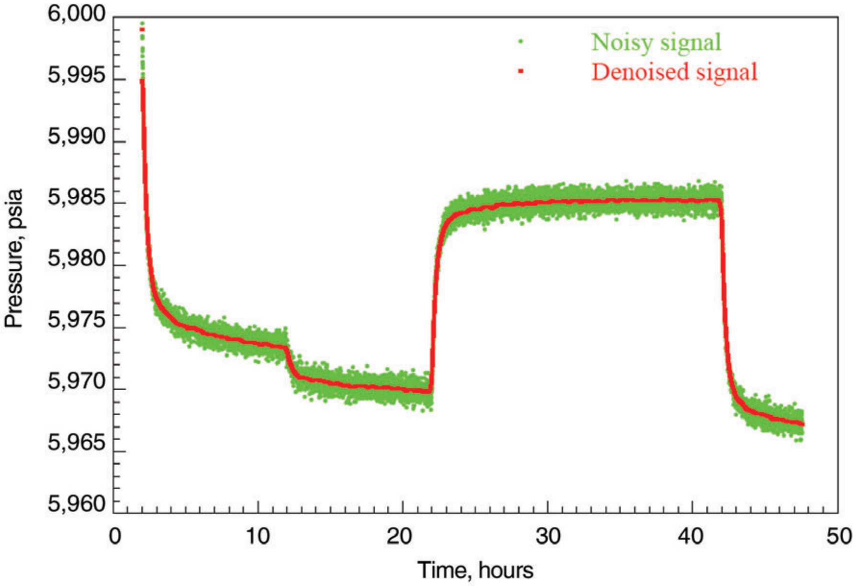

Fig. 1—Example of noise in data, from Athichanagorn (1999).

In spite of the many advantages reported by many authors, several important issues remain associated with the use of data from PDGs. These issues include the following.

- Manipulating and processing large ammounts of data, including the filtering of noise and nonidealities
- Deconvolution of the complex time series into characteristic behaviors
- Identifying breakpoints to separate transients into relevant subsections
- Accommodating changes in well or reservoir parameters (such as permeability and skin) as a function of time
- Handling flow-rate information

Manipulating and Processing Data

Data from PDGs may be recorded as frequently as once per second, over periods of years. Such a frequency of measurement from each gauge would generate approximately 32 million data points per year. The physical storage and access of these volumes of data can be a challenge for management and transfer of the measurements because even modern database applications and analysis software can be overcome by the requirements. Handling such large volumes of data requires careful development of a data-management strategy (Chorneyko, 2006). These issues are topics of investigation.

Even after the volumes of data are recorded, stored, and accessed, significant problems remain in processing the data before they can be used for reservoir analysis. The sequences of events recorded by the PDGs are largely uncontrolled in that they are responses to normal and/or unintentional operational changes in well-flow conditions. The data are subject to various difficulties as described by Athichanagorn et al. (2002).

- Noise
- Outliers
- Behavioral excursions in the response
- Uncertainty regarding transient breakpoints
- Missing flow-rate information

An example of noise in real data is shown in **Fig. 1,** which reveals a band of seemingly random measurement errors of approximately ±1.5 psi (shown in green) surrounding an underlying signal (shown in red) that appears to represent the reservoir-pressure transient.

An example of outliers in real data is shown in **Fig. 2,** which illustrates a large number of points (shown in green) that differ substantially from the underlying signal (shown in black). Some of these single-point data excursions can be as large as 100 psi in the example shown. The exact causes of

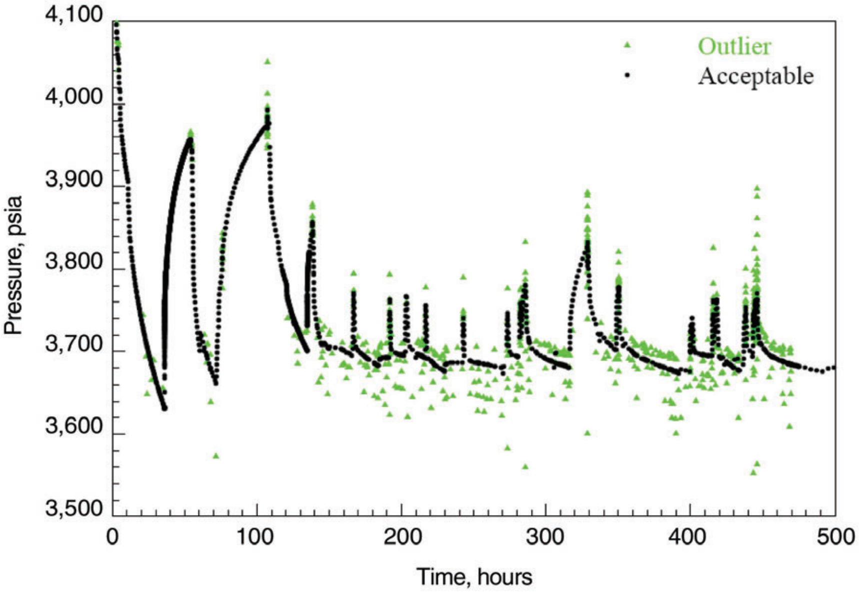

Fig. 2—Example of outliers in data, from Athichanagorn (1999).

these outliers may be of various natures and usually are not known.

An example of behavioral excursions, referred to as aberrant data by Athichanagorn et al. (2002), is illustrated in **Fig. 3.** Certain complete segments of data seem to follow behaviors that are substantially different in character from the other transients. These anomalous transients pose a very significant difficulty during interpretation because both nonlinear regression and deconvolution are adversely affected by these atypical sections of response. Some of these difficulties will be mentioned further in later sections of the paper.

The issues of breakpoint identification and handling of flow rates will be discussed in later sections.

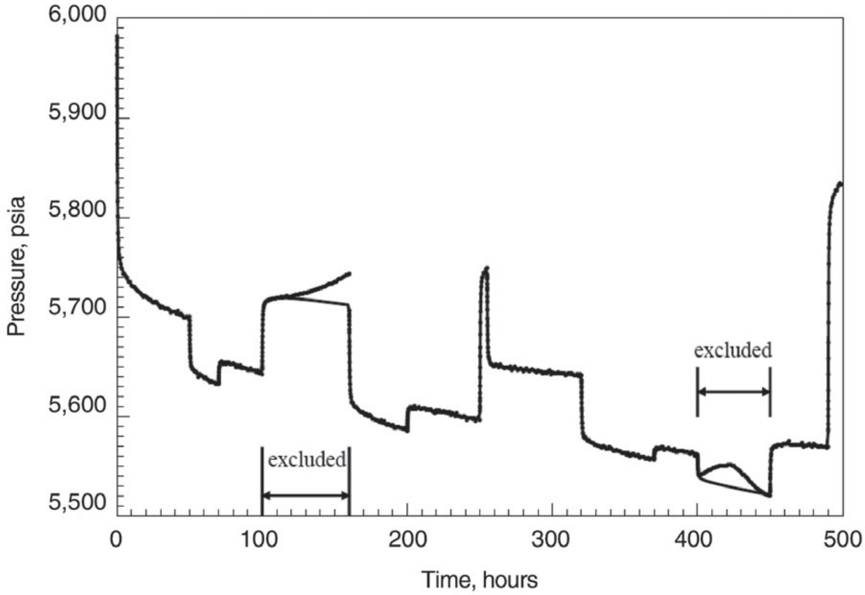

Fig. 3—Example of behavioral excursions in data (indicated as "excluded"), from Athichanagorn (1999).

It is important to note that the first three kinds of deviations—noise, outliers, and behavioral anomalies—are all commonly found in real data recorded by modern PDGs. Although it is a worthwhile target to improve accuracy of the recorded signals, it is to be expected that many of these data excursions are the results of operational variations that occur in the wells. As such, these excursions can be considered an inherent behavior of PDG data and, therefore, must be accommodated within any processing procedure that is applied to those data.

The successful use of wavelet analysis to handle the noise and outliers has been reported by several authors, including Kikani and He (1998), Athichanagorn (1999), Athichanagorn et al. (2002), Ouyang and Kikani (2002), and Ribeiro and Pires (2006). Figs. 1 and 2, from Athichanagorn (1999), showed the successful removal of noise (Fig. 1) and outliers (Fig. 2) from real data, in this case by use of the spline wavelet. Other families of wavelets also are used [see Ribeiro and Pires (2006) for a comparison].

The recognition of aberrant data sections (behavioral excursions) is a more challenging task, and one in which the wavelet approach is less useful. To identify a section of data that differs from other segments, the first requirement is that a data-processing algorithm achieves an underlying understanding of what is "correct." Athichanagorn et al. (2002) achieved this function by use of nonlinear regression to match a reservoir model to segments of data, and then discarding segments that did not match the model to a defined degree of accuracy. Although shown to be successful in several real field case applications, this approach suffers from the difficulty that the reservoir model must be defined in advance. A further problem is that the model itself may change with time, and another common difficulty is that the drawdown sections of the data may behave differently from the buildups. An attempt was made by Thomas (2002) to use the data to define the model, by use of a variety of parametric and nonparametric methods. This approach

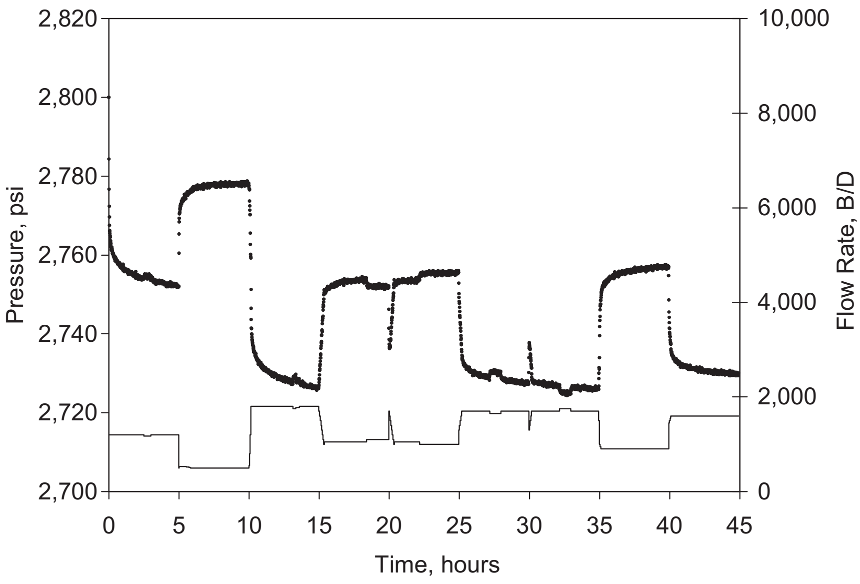

Fig. 4—Example data set with 0.3% noise, from Nomura (2006).

avoids the need to specify a reservoir model in advance. Nomura (2006) suggested the use of the nonparametric regression method—alternating conditional expectation—defined by Breiman and Friedman (1985) as another way to extract the underlying behavior without prior assumption of the functional form of the transient. Although these various approaches have achieved some degree of success, the problem of identifying anomalous patterns in the transient remains a task for investigation.

Deconvolution

Deconvolution is a term used to describe the mathematical manipulation of a complex signal containing complex variable-rate transients, and then to extract from it the underlying simple reservoir response to a single transient. Stating the forward convolution problem, a multiple transient, $\Delta p_w(t)$, can be constructed from individual (constant-rate) transients, $\Delta p_o(t)$, that represent the underlying reservoir model:

$$\Delta p_w(t) = \int_0^t q'(\tau) \bullet \Delta p_0(t-\tau)\,\mathrm{d}\tau. \qquad (1)$$

Here $q'(\tau)$ is the time rate of change of the flow rate, q.

The deconvolution process involves solving the integral equation described by Eq. 1 by use of the measured well-pressure and flow-rate histories to extract the underlying reservoir model, $\Delta p_o(t)$. The reasons for applying the deconvolution process are as follows.

- To be able to identify the nature of the reservoir response that may not be evident in the complex signal
- To extend the range of the effective time of the short transients in the complex signal because the inferred single rate (in theory) covers the entire duration of the measurement

Deconvolution has been a theoretician's playground for several decades, for example van Everdingen and Hurst (1949). The hope of extracting global reservoir information from complex everyday pressure signals has sustained many studies on the subject. In spite of this level of interest, there has been only modest effective success, until recently. The fundamental difficulty with deconvolution is that the convolution integral shown in Eq. 1 represents a mathematical smoothing process, and, consequently, the reversal required in deconvolution is a "desmoothing" that is subject to pathological mathematical instability. In theory, the deconvolved solution to the integral equation can be derived without much difficulty, but in practice, it has proved very much more challenging to apply the procedures to real data.

PDG data represent a new target for deconvolution, in that the measurements are of very long duration. It would be very attractive to be able to take 2 years of data, which might perhaps be made up of multitudinous transients each of a few days duration, and deconstruct the signal to visualize a sin-

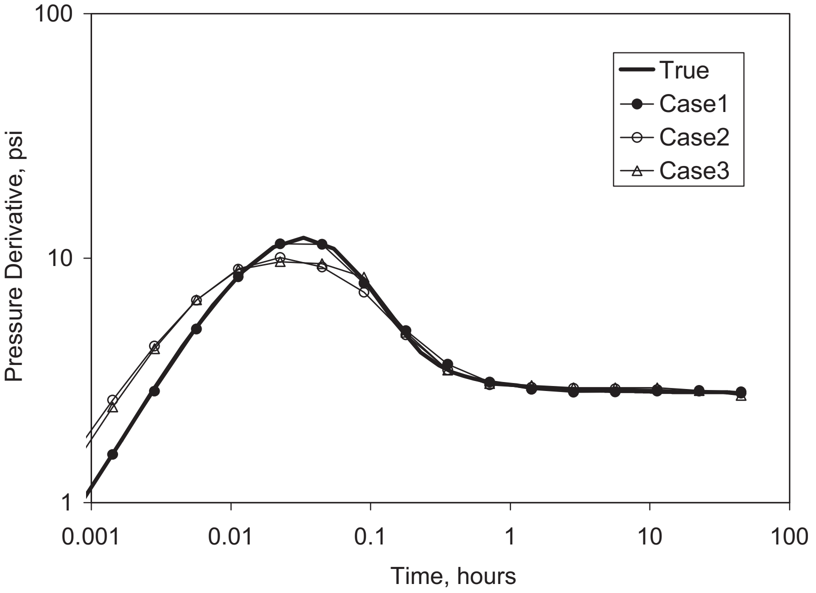

Fig. 5—Deconvolved response, based on the data from Fig. 4. From Nomura (2006).

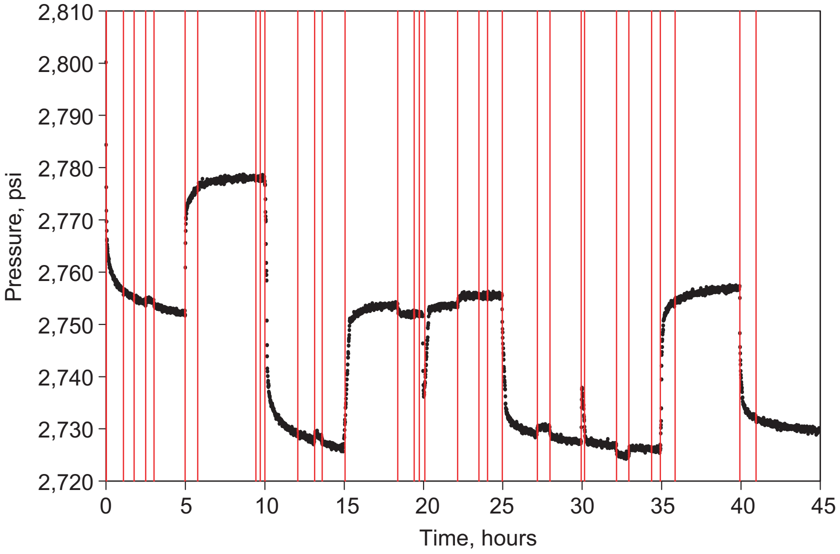

Fig. 6—Breakpoints detected with a wavelet algorithm, using a threshold of 0.01 psi. From Nomura (2006).

gle reservoir-model response that lasted for the whole 2 years. With the increasing availability of this new form of data, researchers revisited the topic of deconvolution in recent years. Importantly, a series of studies by von Schroeter et al. (2004) achieved a practical success with deconvolution that had eluded earlier studies. Among several important innovations in the approach, one was the use of nonparametric methods, which it will be recalled from the previous section was also a useful way of looking for aberrant data segments.

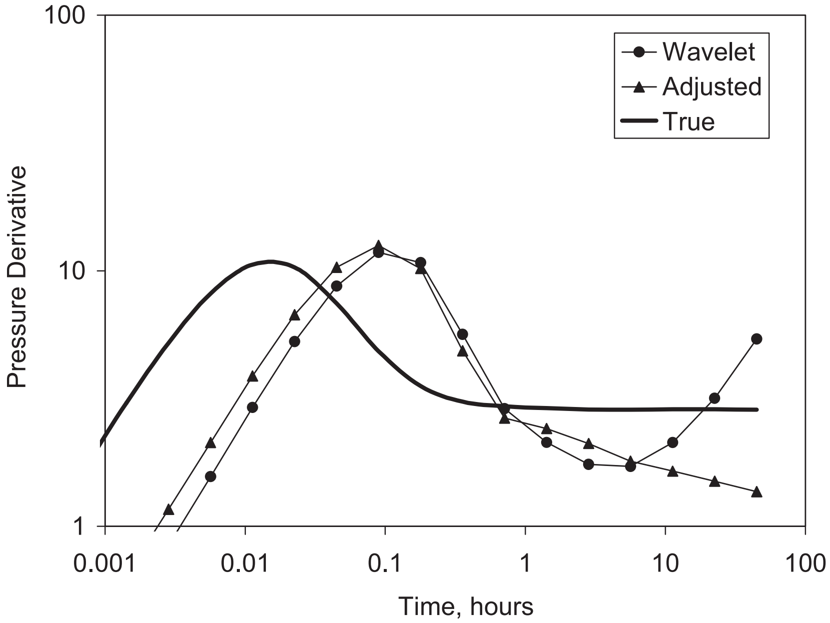

Fig. 7—Deconvolved response of the data from Fig. 4, using the breakpoints detected by wavelet algorithm as shown in Fig. 6. The "true" response is the underlying kernel function used to generate the data in Fig. 4 originally.

On the basis of the original complex transient shown in **Fig. 4,** Nomura (2006) used nonparametric methods derived from those of von Schroeter et al. (2004) to compute the results shown in **Fig. 5.** Importantly, none of the individual transients in Fig. 4 are longer than 5 hours' duration, yet the extracted deconvolved response in Fig. 5 reveals the behavior over the entire 45 hours. Deconvolution allows an expanded view of the reservoir behavior in time and, therefore, provides considerable added value in the context of PDG data compared to a simple analysis of just the individual transients.

Deconvolution is not without difficulties, however. There is an underlying assumption that the reservoir model remains constant throughout the period of the computation. In practice, this assumption is not always valid. One way that the model may change is if the reservoir parameters alter during the extended period of the PDG record—for example, if the permeability and skin do not remain constant. Another difficulty may occur if differences occur during the buildup and the drawdown periods within the continuous record. Differences between buildups and drawdowns are not necessarily unusual, even in short-term wireline well tests, and have been discussed specifically in the context of PDG data by several authors. Levitan (2005) showed advantages of focusing attention on only the buildup sections of the data, an approach also favored by Olsen and Nordtvedt (2006).

Breakpoint Identification

To interpret PDG data for reservoir analysis, it is necessary to break the long-term complex record into its individual transients. This step is required for analysis of the individual transients as if they were separate well tests, but it is also required as an inherent component of deconvolution. Nomura (2006) showed examples in which breakpoint-identification algorithms, which have been published in the past and which are already in use in the industry, gave rise to difficulties when the signals were processed by deconvolution. Even though small inaccuracies in finding the exact breakpoints were not visible by eye **(Fig. 6),** these inaccuracies have a severely detrimental effect on deconvolution. **Fig. 7,** from Nomura (2006), shows the deconvolved response using two forms of breakpoint identification, first the wavelet approach described by Athichanagorn (1999) and second a manual adjustment of the algorithmically determined points to remove those that are visually false. Also shown in Fig. 7 is the "true" response, which is the kernel function, used originally to generate the data for Fig. 4. What is striking about Fig. 7 is the dramatic effect of very small inaccuracies in the breakpoints. The final inference of the reservoir model is quite different from the true behavior, and changes markedly depend on small variations in the algorithm. This synthetic case allows us to see that the reservoir model has not been recovered, but in real data this would be impossible because the reservoir model is unknown (in fact, our objective is to discover it).

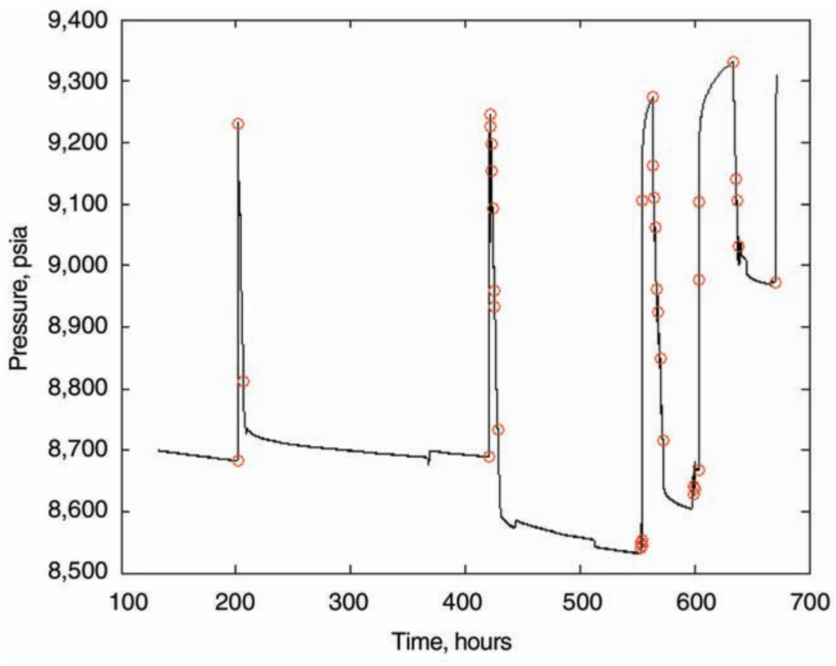

Fig. 8—Application of Savitzky-Golay smoothing filters to the breakpoint identification. Most visually apparent breaks are detected correctly, but some are missed (e.g., at 375, 440, and 515 hours). From Rai (2005).

Kuchuk et al. (2005), who noted the effect on rate/time deconvolution of the value assumed for the initial pressure, implied another manifestation of the breakpoint issue. The breakpoint problem also was described as "event identification and synchronization" by Haddad et al. (2004).

One way to estimate the location of breakpoints is application of wavelet transformation, as described by Athichanagorn (1999), Athichanagorn et al. (2002), and Ouyang and Kikani (2002). Fig. 6 showed the application of the wavelet approach, using the data from Fig. 4. It can be seen in Fig. 6 that most of the visually apparent breakpoints have been detected, although a considerable number of extraneous ones also have been added. In practical applications of this approach, it is not uncommon that real breakpoints can be missed. One of the difficulties is that the method requires the specification of a threshold level at which a data event (in wavelet space) can be considered a breakpoint. The appropriate value of the threshold depends on the level of noise in the signal, which can be difficult to determine. Khong (2001) used a statistical approach to this problem, running the breakpoint algorithm over a range of threshold levels and selecting the breaks that were indicated most frequently. Nonetheless, the extended methodology still failed to recover all real breakpoints reliably, and did not avoid the addition of extraneous ones.

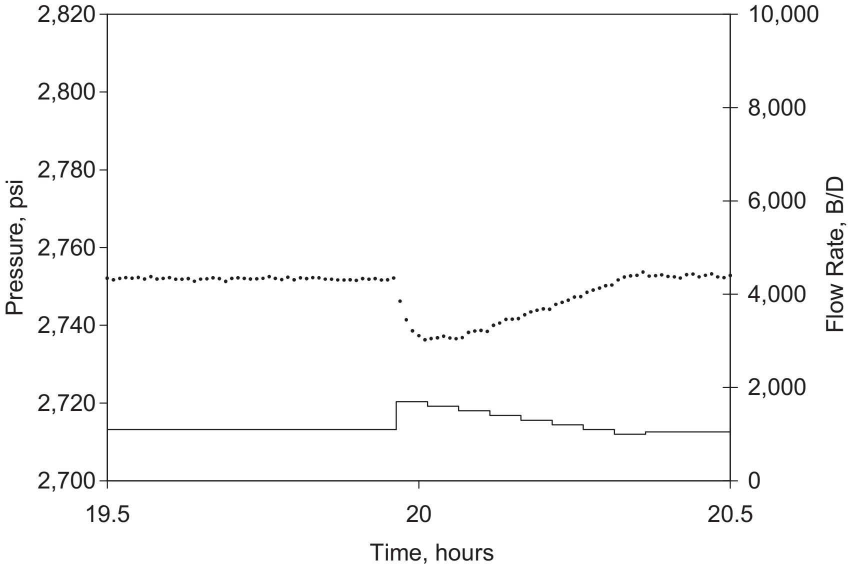

Fig. 9—A "soft" transition in pressure and flow rate. Section of data extracted from Fig. 4. From Nomura (2006).

Rai (2005) experimented with some nonwavelet methods, namely the Savitzky-Golay smoothing-fil-

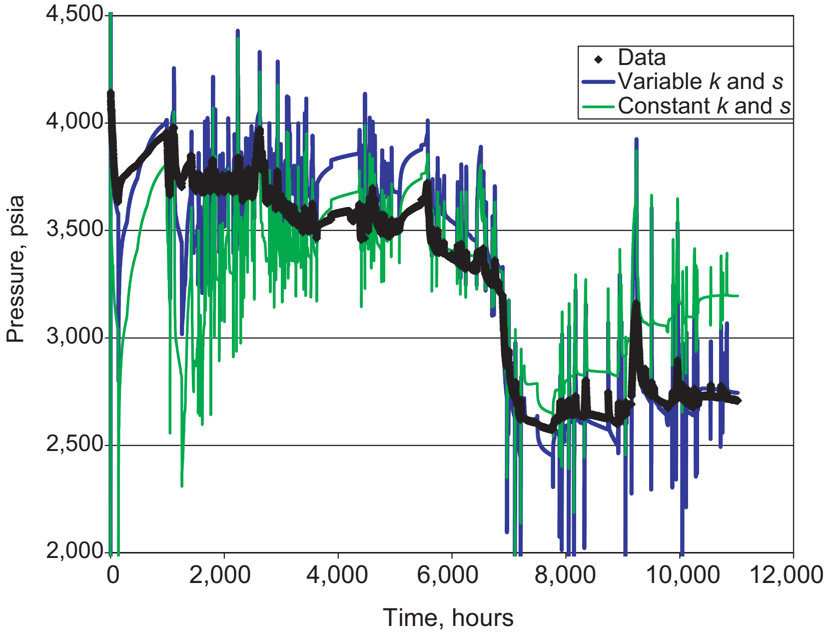

Fig. 10—Attempting to match a 2-year record of data (black points) is not possible using a model with constant* k *and* s *(green points). Using variable* k *and* s *(blue points) results in a much more convincing match. From Lee (2003).

ter approach shown in **Fig. 8.** This method also was successful in determining most visually apparent breakpoints, but like other methods sometimes missed some and sometimes added extraneous ones. Rai (2005) also introduced a pattern-recognition approach he called the segmentation method, as well as a variant that was able to improve the recognition of the breakpoints by use of simultaneously measured flow-rate data. Olsen and Nordvedt (2005), described a different pattern-matching method by use of pressure data alone.

One reason that breakpoint detection is so challenging in real data is that the breakpoints themselves are often "soft." Instead of being a sharp transition from one trend to another, often they are a slow evolution. This issue was illustrated very clearly in Fig. 6 of Coludrovich et al. (2004) in real PDG records from the Boris field. A segment of the synthetic example from Fig. 4 (from Nomura, 2006), illustrated in expanded view in **Fig. 9,** shows a similar style of soft transition.

Nomura (2006) had success identifying the difficult soft breakpoints. Beginning with a set of break points suggested by the wavelet approach, Nomura (2006) used the Powell criterion to determine whether the indicated points were sufficient. In areas with modeled pressures beyond the acceptable difference from measured data, new breakpoints were inserted. Importantly, Nomura (2006) also introduced a subsequent step of breakpoint deletion by which redundant points, or ones that resulted in local overfitting, were removed. These procedures resulted in much better determination of breakpoints and, for example, made it possible to render the true reservoir model. Fig. 5 showed Nomura's successful inference of the reservoir model once the breakpoints were established correctly with his insertion/deletion approach. This result should be compared with Fig. 7, which showed that even small inaccuracies in the inferred breakpoints resulted in large errors in inferring the reservoir model.

Breakpoint detection has been found to be a difficult problem, although good progress toward solving it has been made by use of approaches described here. Research on the topic continues.

Changes in Reservoir Properties and Well Condition

When working with PDG data, the reservoir engineer might try early on to determine the reservoir model. The model is useful to characterize the reservoir and must be known if the data are going to be matched as a way of inferring the values of unknown reservoir parameters. One way to deduce a model is by deconvolution, if the breakpoints have been determined correctly. Another way is to separate an individual transient from the sequence and interpret its behavior in the conventional sense, as if it were a standard well test.

It is common, although in principle not strictly necessary, to assume that the reservoir model does not change with time. Although this may be reasonable in a conventional well test, which lasts a few hours or a few days, the assumption is not trustworthy in the case of long-term records from PDGs. Skin factor and effective permeability change during the months and years of data recorded by the gauge. These changes must be addressed in the interpretation of PDG data.

This point was noted by Athichanagorn (1999) and by Khong (2001). The actual data from which their estimates were made came from a real 2-year PDG record, as shown in **Fig. 10.** Lee (2003) examined the same data and treated the permeability and skin factor, *k* and *s*, respectively, as explicit functions of time. Fig. 10 illustrates how a treatment of the permeability and skin factor as constants results in a poor replication of the measured pressure, whereas a time-varying representation of permeability and skin factor provides a more convincing match.

The variation of permeability and skin as functions of time has been noted in real field cases by several authors, including Richardson et al. (2002); Haddad et al. (2004); Coludrovich et al. (2004); Chorneyko (2006); and Olsen and Nordtvedt (2006). Olsen and Nordtvedt (2006) in particular made note of the difficulty in obtaining reliable skin estimates because of the lack of acceptable confidence intervals.

Although the variability of reservoir parameters as a function of time is difficult as described in several papers, de Oliveira Silva and Kato (2004) made a broader observation that encapsulates this effect, that analytical models traditionally used for conventional well-test interpretation often may be too simple to define the pressure and flow-rate transients that occur during the extended duration of a PDG record. This issue is clearly understood by many, yet the published applications of full-field multiphase-flow simulation (using a numerical reservoir simulator) to the interpretation of PDG data have been few. The complexities inherent in PDG data may make applying complex models difficult until the issues of data filtering, model recognition (or model-nature recognition), and transient identification have been solved reliably. Even though the results summarized here appear very promising, it also is apparent that additional improvement will require further research and development.

Measurement of Downhole Flow Rate

Although permanent downhole pressure gauges have been used for some time, it is uncommon to pair them with permanent downhole flow rate gauges. Measuring flow rates downhole could reduce the uncertainty of events happening in the reservoir, and measuring the flow rate directly could address the issue of identifying breakpoints. Some examples of the use of downhole flow rate measurements have begun to appear in the literature [e.g., Coludrovich et al. (2004)].

However, data from permanent downhole flow-rate gauges have their own difficulties. Measurements are subject to some of the same kinds of noise and outlier issues described for permanent downhole pressure measurements. Von Schroeter et al. (2004) showed the advantage of specifically associating an uncertainty with the flow-rate data instead of treating the measured flow-rate information as absolute truth and matching the pressure data (as is normal practice in a conventional well-test interpretation). They made use of a total-minimization approach that matched measured pressures and flow rates at the same time. Nomura (2006) followed a similar line.

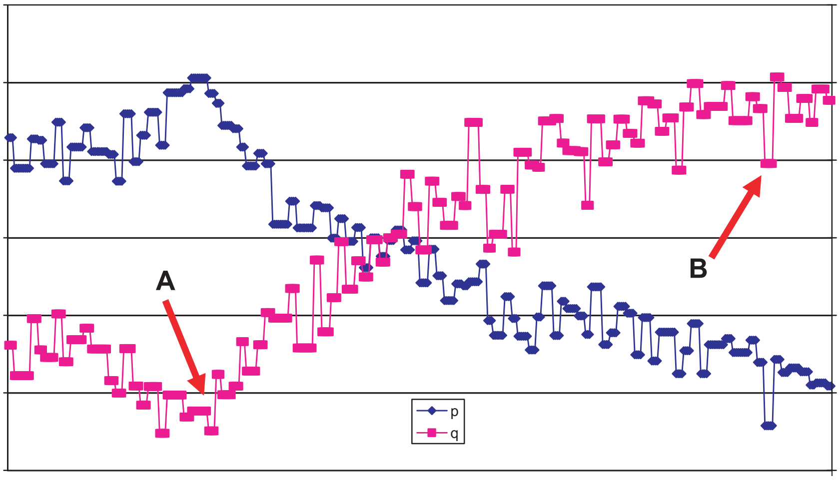

Fig. 11—A 5-minute segment of pressure and flow rate data from a PDG that recorded at 1-second frequency. Arrow A indicates a flow-change event; Arrow B represents a noise event.

Rai (2005) used a different approach in combining the flow-rate information as a way of recognizing the breakpoints. Measured flow-rate data are used to help define segments of data that bend upward or downward.

Including data from permanent downhole flow rate tools remains an area of active research. One way in which flow rate data may be useful is identifying which parts of the pressure signal are attributable to noise. **Fig. 11** shows a segment of data from a PDG that measured both pressure and flow rate at 1-second frequency. The segment includes only approximately 5 minutes of data. The arrow marked "A" shows an obvious flow-rate change event, in that the flow rate increases and the pressure correspondingly decreases. The arrow marked "B" shows a noise event because the pressure and flow rate signals both drop simultaneously (whereas reservoir physics would have them move in opposite directions). Simultaneous consideration of the data may enable obtaining a clearer understanding of the signal than would be possible by analyzing either of the signals alone.

Summary

PDGs have become very useful tools for reservoir characterization, although it must be acknowledged that development of the devices themselves has surpassed development of methods and algorithms to manage and interpret the data. If the industry is to make best use of these abundant sources of data, development of management and analysis tools must continue. The huge volumes of data must be stored in a manner that allows efficient access and recovery—a requirement that challenges even recent bandwidths. Interpretation of such numerous measurements is no longer a task that can conceivably be achieved only by human interaction with the data—a set of reliable automated algorithms will be necessary to gain maximum advantage.

Progress toward achieving the necessary data-management and -interpretation tools has been promising, as evidenced by results reported in recent literature. Nonetheless, the problems are not yet fully solved, and research in this area is appropriately active.

Acknowledgments

This review made use of the results of many authors listed in the reference list, yet the literature on PDGs is far more extensive than can conveniently be included here. The omission of other important papers on the subject has only been in the interest of space. The support of the SUPRI-D research consortium on innovation in reservoir testing is gratefully acknowledged.

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