MINIMIZATION OF THE NOISE IN THE CALCULATED PRESSURE DERIVATIVE DATA FOR THE INTERPRETATION OF TRANSIENT TESTS

ABSTRACT

Well tests are conducted to estimate essential reservoir parameters like permeability and skin factor. Pressure data is recorded at regular intervals during these tests, which are crucial for predicting the production potential of oil or gas. Analyzing pressure changes provides insights into the reservoir's characteristics and its ability to produce hydrocarbons over time.

Three different cases of drawdown tests are examined, and derivative curves are plotted using data points separated by specific intervals, ranging from 0.10 to 0.50 of a log cycle. This interval selection is vital to avoid excessively noisy derivative values during differentiation. A novel method is developed to determine the log cycle interval that minimizes noise while maintaining the integrity of the derivative curve. Additionally, second and third derivatives are calculated for each log cycle interval to identify the most suitable one.

The log cycle interval helps identify early, middle, and late-time regions, representing different flow regimes in both cases. The data from the middle time region is selected for the estimation process, as it offers the best estimates of permeability. These results are then compared with those obtained from KAPPA's Saphir Module, an industry-standard PTA (pressure transient analysis) module. The Python code used for estimation is found to provide more accurate estimations of permeability and skin factor and can handle noises up to ±2.5%.

Keywords: Derivative Plots, Pressure Transient Analysis

STATEMENT OF THE PROBLEM

In petroleum engineering, determining reservoir parameters such as permeability, porosity, and skin factor is of utmost importance. Accurate determination of these parameters is essential for conducting feasibility analyses because significant amounts of money are invested in the discovery and development of reservoirs. Well testing provides valuable data for evaluating and optimizing production, making the accuracy of this data critical for decision-making and feasibility assessments. To make informed decisions, it is crucial to have a clear understanding of reservoir parameters, especially permeability and skin factor.

Despite efforts to ensure the reliability of well test data, uncertainties persist due to factors like multiphase flow measurement and complex fluid flow dynamics. These uncertainties introduce noise in the data, necessitating their elimination to make the most informed decisions.

Derivative plots offer valuable insights into reservoirs, but calculating pressure derivatives is a delicate process as it can easily amplify the existing noise in the data. Various new methods are employed to estimate these parameters, incorporating recent technological advancements to enhance accuracy and minimize predictive errors.

METHODOLOGY

i) Noise Elimination of Derivative Plots

In 1983, Bourdet et al. introduced derivative plots, which were regarded as the most valuable diagnosis tool at that time, as mentioned by Horne (1995).

Calculating pressure derivatives is a delicate procedure due to the risk of amplifying noise in the data. Several differentiation methods can be employed, and one such method involves numerically differentiating adjacent points using Eq 1. However, this approach is rarely used in well test analysis because it leads to very noisy derivative values.

$$t\left(\frac{\partial P}{\partial t}\right)_i = t_i\left[\frac{(t_i - t_{i-1})\Delta p_{i+1}}{(t_{i+1} - t_i)(t_{i+1} - t_{i-1})} + \frac{(t_{i+1} + t_{i-1} - 2t_i)\Delta p_i}{(t_{i+1} - t_i)(t_i - t_{i-1})} - \frac{(t_{i+1} - t_i)\Delta p_{i-1}}{(t_i - t_{i-1})(t_{i+1} - t_{i-1})}\right] \qquad \text{Eq 1}$$

It is suggested in the literature that numerical differentiation with respect to natural logarithm of time by using Eq 2 would reduce the noise in the derivative calculation compared to the previous method.

$$t\left(\frac{\partial P}{\partial t}\right)_i = \left(\frac{\partial P}{\partial \ln t}\right)_i = A + B - C$$

where

$$A = \frac{\ln\left(\frac{t_i}{t_{i-1}}\right)\Delta p_{i+1}}{\ln\left(\frac{t_{i+1}}{t_i}\right)\ln\left(\frac{t_{i+1}}{t_{i-1}}\right)} \qquad \text{Eq 2}$$

$$B = \frac{\ln\left(\frac{t_{i+1}t_{i-1}}{t_i^2}\right)\Delta p_i}{\ln\left(\frac{t_{i+1}}{t_i}\right)\ln\left(\frac{t_i}{t_{i-1}}\right)}$$

$$C = \frac{\ln(t_{i+1}/t_i)\Delta p_{i-1}}{\ln(t_i/t_{i-1})\ln(t_{i+1}/t_{i-1})}$$

Using data points that are at least 0.2 of a log cycle apart instead of adjacent points while differentiating with respect to the natural logarithm of time can result in further noise reduction. However, this method has a limitation: it may lead to a lack of data during the first and last differentiation intervals. So the third differentiation method is

$$\boldsymbol{t\left(\frac{\partial p}{\partial t}\right)_i = \left(\frac{\partial p}{\partial \ln t}\right)_i = A + B - C}$$

Eq 3

$$\boldsymbol{A = \frac{\ln(t_i/t_{i-k})\Delta p_{i+j}}{\ln(t_{i+j}/t_i)\ln(t_{i+j}/t_{i-k})}}$$

$$\boldsymbol{B = \frac{\ln(t_{i+j}t_{i-k}/t_i{}^2)\Delta p_i}{\ln(t_{i+j}/t_i)\ln(t_i/t_{i-k})}}$$

$$\boldsymbol{C = \frac{\ln(t_{i+j}/t_i)\Delta p_{i-k}}{\ln(t_i/t_{i-k})\ln(t_{i+j}/t_{i-k})}}$$

where

$$\boldsymbol{\ln t_{i+j} - \ln t_i \geq 0.2}$$

$$\boldsymbol{\ln t_i - \ln t_{i-k} \geq 0.2}$$

Horne (1995) mentioned that the differentiation interval could be substituted with values ranging from 0.1 to 0.5, depending on the specific case.

During the differentiation of late-time data, the distance between data points becomes larger than the last data point and the previous differentiation point. This phenomenon, known as the end effect, prevents smoothing on the right side and may distort the shape of the derivative curve. Bourdet et al. (1989) proposed a solution to this issue by introducing a pseudo point to the right and fixing it. The difference (ΔX) between the pseudo point and the point before it should be greater than or at least equal to this length.

A Python code was developed to process pressure and time data. It calculates derivative values using data points separated by a proportion of a log cycle, ranging from 0.10 to 0.50, with increments of 0.01. As a result, 41 different derivative values with various separation intervals are computed.

ii) Selecting the Smoothest Derivative Plot

The aim is to find the best log cycle interval among the 41 different intervals(between 0.10-0.50), the one that eliminates the most amount of noise without overly smoothing the derivative plot. In order to be able to do that Python is used.

Second and third derivative values are calculated for every one of the 41 different derivative values. Number of sign changes in the second and third derivatives are calculated separately and divided to the total number of data points.

For example when using 0.26 log cycle intervals,

Number of sign changes is 2 for the second derivative values and 8 for the third derivative values, meaning that there are 8 different inflection points. There are 53 data points in total and the ratio for the second derivative is:

$$\frac{Number\ of\ sign\ changes}{Number\ of\ data\ points} = \frac{2}{53} = 0.03774$$

And the ratio for the third derivative is:

$$\frac{8}{53} = 0.15094$$

0.31 interval has the lowest sum of ratios among the all 41 second derivative values and all 41 third derivative values meaning that it is the smoothest of them. For all three of the cases, it is proven that the best intervals are the ones that have the smallest sum of sign change ratios of second and third derivatives.

iii) Determination of the Middle Time Region

In the early time region, the flow behavior in and around the wellbore, including effects like wellbore storage and formation damage/stimulation, plays a dominant role in the fluid flow. As time progresses, the flow is expected to transition to infinite-acting behavior in the middle time region, assuming a homogeneous reservoir. In this region, the pressure derivatives are expected to be horizontal.

Having identified the optimal log cycle interval that provides a derivative plot with minimal noise and appropriate smoothing, our focus is now on determining the middle time regions. These regions are crucial for obtaining the most accurate estimates of permeability (k) and skin factor (S).

For all drawdown cases, infinite acting radial flow is observed during the middle time regions, resulting in horizontal derivative curves. Specifically, the first derivative values remain relatively constant, and the second derivative values approach zero.

To identify the middle time regions, Python is employed once again, and all three derivatives (first, second, and third) are analyzed. We locate the region that follows a specific inflection point, where the first derivative values are relatively constant and the second derivative values fall within the range of -100 to +100. This constraint is incorporated into the Python code to facilitate the selection of points that come after the inflection point.

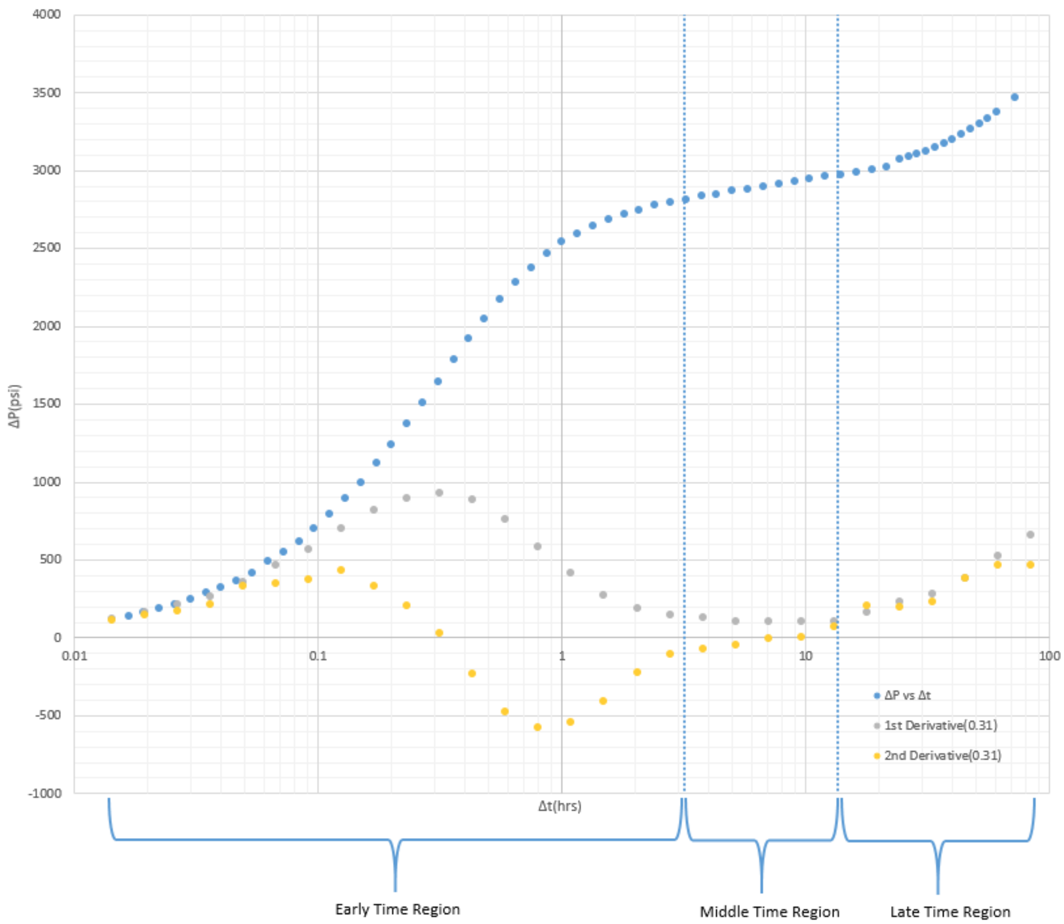

Figure 1 Middle Time Region Estimation for Drawdown Case I. Cosar(2022)

Up to this point, we have identified the flow regions of early time, middle time, and late time, as depicted in the figure above. The semi-log plot provides a clear indication that the time region estimations are precise for Drawdown Case I.

iv) Permeability and Skin Factor Estimation

Once more, Python is employed to estimate the permeability and skin factor using the graphical analysis method, utilizing the data points obtained from the middle time region estimation.

A semilog plot of pressure (P) versus time (t) is generated using Python. A best-fitting line is drawn through the points corresponding to the middle time region. By calculating the slope of this line, referred to as "m," the permeability can be estimated using the following equation

$$\boldsymbol{k = -162.6\frac{Q \times B \times \mu}{m \times h}} \qquad \text{Eq 4}$$

In order to estimate the skin factor, S, following equation is used.

$$\boldsymbol{s = 1.151\left[\frac{P_i - P_{1hr}}{|m|} - \log\frac{k}{\phi\mu c_t r_w^2} + 3.2274\right]} \qquad \text{Eq 5}$$

It should be noted that for the P_{1hr} value, the point on the semi-log straight line should be used rather than the measured P value at 1 hour.

RESULTS

The study demonstrates that the noise in derivative plots can be eliminated by identifying the optimal log cycle interval and using it during pressure derivative calculations. Pressure derivatives are considered highly valuable for diagnosing well test analysis. By improving the accuracy of time region identifications, the estimations of permeability and skin factor are enhanced. These stand correct for three different drawdown tests.

The estimation process utilizes a graphical analysis method, which results in minimal error and performs calculations rapidly, completing them within seconds.

It is shown that the Python code written can estimate permeability and skin factor in three different drawdown cases more accurately than KAPPA's Saphir Module, an industry standard Pressure Transient Analysis tool, as can be seen from Table 1.

Table 1 Absolute Error Percentages of Different Methods

Case	Graphical Analysis Method	KAPPA's Saphir Module
Drawdown I	0.915%	1.243%
Drawdown II	1.946%	3.900%

Another drawdown test data with known parameters(k=40 md, S=+2.90) had been generated and to test the methods tolerance to noise, random artificial Gaussian noise of ±0.5%, ±1%, ±1.5%, ±2%, ±2.5%, ±3% is added to the Drawdown Case III pressure data. The Python code had been run 20 times for each case. Confidence interval of 95% is used for the calculations. It is seen that the Python code can handle noises up to ±2.5%.

Table 2 Permeability and Skin Factor Estimations with Randomly Added Noises

Parameter	±0.5%	±1%	±1.5%	±2%	±2.5%	±3%
k(md)	39.365	39.893	39.825	41.424	40.746	37.050
S	2.758	2.973	2.833	3.133	3.086	2.170

CONCLUSION

Well testing provides valuable data for evaluating and optimizing production, making it a crucial aspect of reservoir management. The accuracy of this data is essential for understanding the reservoir's characteristics and making informed decisions accordingly.

Flow period identification is the initial and arguably the most critical step in well test analysis. Derivative plots, which are diagnostic plots, play a vital role in this identification process, and their reliability directly impacts the accuracy of permeability and skin factor estimates.

Although pressure and flow rate measurement technology has improved, some level of noise persists in most well test data and must be addressed before performing reservoir characterization and parameter estimation processes.

The Python code developed in this context has demonstrated the ability to handle noise up to ±2.5%. It also provides more accurate estimations of permeability and skin factor compared to an industry standard PTA software tool, KAPPA's Saphir Module.