Analysis of Relatively Short Variable Rate "Noisy" Well Test Data Using Non-Linear Deconvolution

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Abstract - Short well test data are pressure-rate-time data that are not long enough to be used to infer the reservoir boundary model and are very common in the oil and gas industry. Short rate well test data may occur when companies try to cut costs of well test jobs or mostly due to improper well test design. Nevertheless, one may wish to extract the most amount of information from this limited data because the de-convolve response can allow the reservoir engineer to make the best use of the available data in selecting a suitable interpretation model by narrowing down the possible boundary models and also providing a reliable estimates of model parameters. The aim of this study is to demonstrate the usefulness and significance of pressure-rate deconvolution in analyzing relatively short variable rate data using a hypothetical case study. The simulation was carried out using Sapphire's test design module by assuming the presence of an exploratory well in an oil reservoir above bubble point pressure. Further assumption is that the reservoir is homogenous, therefore the possibility of a changing wellbore model was neglected from the analysis. The computer codes for the simulation were inputted using python programming language. We observed from the study that although pressure and flow rate relationship can be nonlinear, the problem can be formulated as a linear problem and the nonlinearity is expressed in the features of the reservoir. The simulation results were satisfactory using the test case and deviations between model parameters and actual reservoir parameters used in simulation was shown to have an absolute value less than 8% which is within acceptable engineering limits.

Keywords: Pressure-transient, Reservoir boundaries, Semi-infinite, Sapphire, Pressure build-up

1. Introduction

In well test interpretation the selection of a well interpretation model involves the selection of flow regimes for each component of the interpretation model. For example, a reservoir interpretation model may be selected to have skin and wellbore storage effects as the inner boundary effects, a homogeneous reservoir behavior, and a constant pressure outer boundary [5].

Proper diagnostic tools are needed in order to identify the different flow regimes which may occur in each component of the interpretation model. Researchers over the years have proposed several techniques (diagnostic tools) for identification of various flow regimes in a well test; specialized plots, pressure-time (log-log) plot and pressure derivative diagnostic plot [3].

These diagnostic tools have some limitations when applying them to variable rate well test data. For example, the pressure in the pressure derivative diagnostic plot, due to the way it is computed amplifies the errors in recorded data; this may lead to generation of artifacts when applied to noisy data [1]. The straight-line plot and flow regime specific plots have errors in selecting the boundaries of the region of the data that shows straight line trend which corresponds to a specific flow regime [3]. All three mentioned diagnostic plots share the constraint that their radius of investigation (the distance the pressure disturbance has travelled into the reservoir) is limited by the longest time in the flow history [8].

Therefore, a technique is needed which takes measurement of noise into account and allows the reservoir engineer to see deeper into the formation in order to enable him select the most appropriate interpretation model that fits the data. This is where pressure-rate deconvolution becomes useful and convenient. Deconvolution is simply the inverse of convolution. It involves the determination of the unit pressure response or the impulse pressure response from the given rate history and well pressure response [8]. Deconvolution is not a new technique that replaces conventional techniques, rather it was introduced to be used alongside conventional techniques.

Nonlinear deconvolution involves fitting a nonlinear response to the variable rate pressure data. It was introduced due to the short comings of previous deconvolution techniques. Nonlinear deconvolution can be helpful in inferring the boundary model in the case of relatively short well test data.

There have been several attempts in literature at deconvolution but all failed considerably when applied to data with considerable noise in rate measurement. Schroeter, Hollaender and Gringarten [8] were the first to account for the effects of large noise in rate measurement on the deconvolution algorithm for linear problems. They formulated the deconvolution problem as a non-linear total least squares (TLS) problem or what in statistics is referred to as an error in variables problem. Their method makes use of the variable projection algorithm to deconvolve the rate and pressure history. However, as pointed out by Levitan [6], the Von Schroeter [8] formulation can only be applied to data with constant wellbore model (i.e. constant skin and wellbore storage) and will not produce satisfactory results when applied to a varying wellbore model.

Levitan [6] developed a new pressure rate deconvolution algorithm to analyze real test data (data which are characterized by changing skin, changing wellbore storage or both). Their implementation is quite different from that of Schroeter, Hollaender and Gringarten [8] in that they applied the algorithm for unconstrained minimization to minimize their objective function and their formulation also allows the selection of specific flow periods to be included in the model parameters [2]. The author suggested that in the case of different skin and wellbore storage for different flow periods the deconvolution should be performed separately on each buildup assuming a value of initial reservoir pressure for each buildup. The initial reservoir pressure is then changed manually until the several deconvolve build-ups have the same value of initial reservoir pressure. The process of manually changing the initial reservoir pressure can be very tedious and also, since their method is conducted on each build-up separately it may lose information about intermediate behaviors [4].

Von Schroeter, Hollaender and Gringarten [9] modified their earlier proposed model. The modified algorithm is similar to that which was originally published except that penalization of smoothness was based on total curvature instead of average slope. They also provided a rigorous error analysis of the method.

Houze, Tauzin and Allain [4] discussed a new technique of deconvolution similar to that of Von Schroeter, Hollaender and Gringarten [9]. Their technique is capable of carrying out deconvolution on a selected reference build-up and the data after the convergence time of other build-ups. The convergence time is the time beyond which the pressure derivative converges. Unlike the Levitan [6, 7] method their method does not require tedious manual iterations for initial reservoir pressure and can produce reservoir responses intermediate between two build-ups.

2. Methodology

The simulation was carried out using Sapphire's test design module. A synthetic downhole gauge data was simulated for our case study, which is a vertical well with constant skin and wellbore storage producing at varying rate in a semi-infinite reservoir at some distance to a sealing fault. The reservoir is homogenous and is assumed to be producing above the bubble point pressure throughout the test in order for the linearity assumption for Duhamel's equation to be obeyed.

The rate history input to the model is shown in Table 1 and consists of four build-up and eleven drawdown rates with each test period (period of constant rate) selected to be of equal duration for simplicity. Table 2 shows the fluid properties. The fluid properties were arbitrarily chosen to be constant, since the reservoir was assumed to be producing above bubble point. The rock properties and other input parameters for the simulation model were arbitrarily chosen as shown in Table 3. Random noise was inputted to both the flow rate history and the simulated pressures using the Pandas and NumPy packages in the python programming environment. For the rate history a noise of zero mean with a standard deviation of 5bbl/day was added to the signal, while for the simulated pressure a noise of zero mean with a standard deviation of 1 psi was added.

Table 1. Rates history

Duration	Liquid Rate
(hr)	(STB/D)
42	140
42	0
42	109
42	196
42	0
42	99
42	152
42	202
42	242
42	0
42	207
42	101
42	204
42	292
42	0

Table 2. PVT parameters

Fluid property	Value	Unit
Formation Volume Factor	1.2	bbl/STB
Viscosity	2.3	cp
Total compressibility	3.00E-06	psi^{-1}

Table 3. Rock properties and other model input parameters.

Parameter	Value	Unit
Skin	3.23	-
Flow capacity (Kh)	396	md.ft
Wellbore storage coefficient	0.00972	bbl/psi
initial reservoir pressure	4996.9	Psi
Well radius	0.25	Ft
Pay zone thickness	30	Ft
Porosity	0.20	%
Distance to fault	409	Ft

Conventional well test interpretation was first carried out on the noisy data, then deconvolution was then applied to all build-ups of the noisy data using Sapphire's deconvolution module assuming all other parameters are known except initial reservoir pressure, skin, wellbore storage, flow capacity and distance to fault.

The deconvolution was performed on all extracted build-ups at once using the algorithm developed by Von Schroeter, Hollaender and Gringarten [9] because the well was said to have a constant skin and wellbore storage coefficient. The Deconvolution was performed with a smoothing coefficient of 0.5, rate relative weight of 1 and pressure relative weight of 10. Several plots of the build-up sections for the simulated data (noisy data) and the deconvolve data were generated and analyzed.

3. Results and Discussions

Figure 1 shows the plot of the simulated pressure response and rate history input. From this figure we can see that there are no negative pressures, this means that the reservoir was capable of producing at the rates indicated in the rate profile.

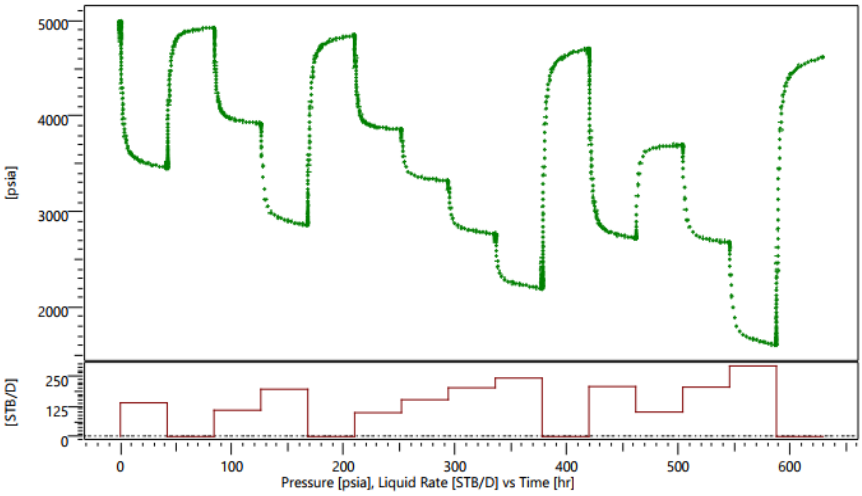

Figure 1. Simulated pressure response and rate history input

Figure 2 shows the log-log plot of pressure change and pressure derivative for the four extracted build-ups. The difference in the plots can be attributed to the different flow rates before each shut-in. The rate normalized plots for the four buildups shown in Fig. 3 confirms this since the plots lay on each other. This plot also shows that the simulated data has a constant wellbore model (i.e. constant skin and wellbore storage).

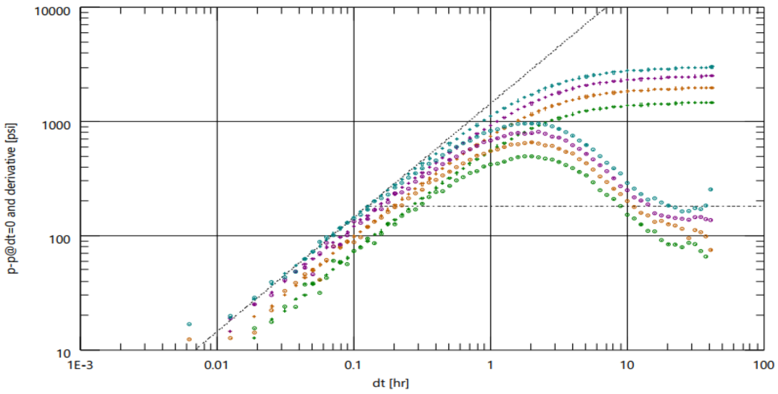

Figure 2. Pressure and Pressure derivative plot

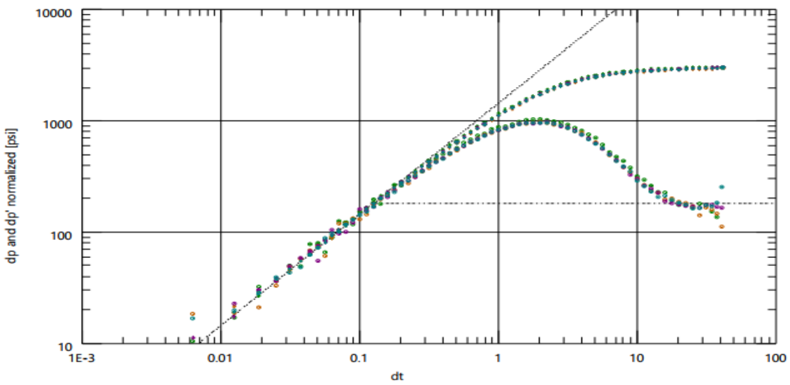

Figure 3. Rate normalized pressure and Pressure derivative plot

Similarly, the same can be seen in Fig.4 and Fig.5 which are non-normalized and rate normalized superposition plots for the four buildups. But unlike the rate normalized log-log plot the rate normalized superposition plot does not overlay one another but instead there is a shift. The shift can be attributed to the difference in pressures at the instant of shut-in for the four build-ups.

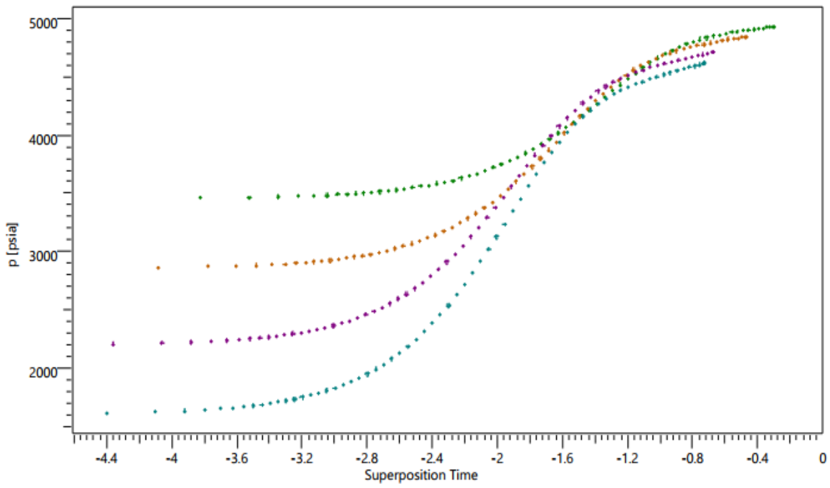

Figure 4. Superposition plot

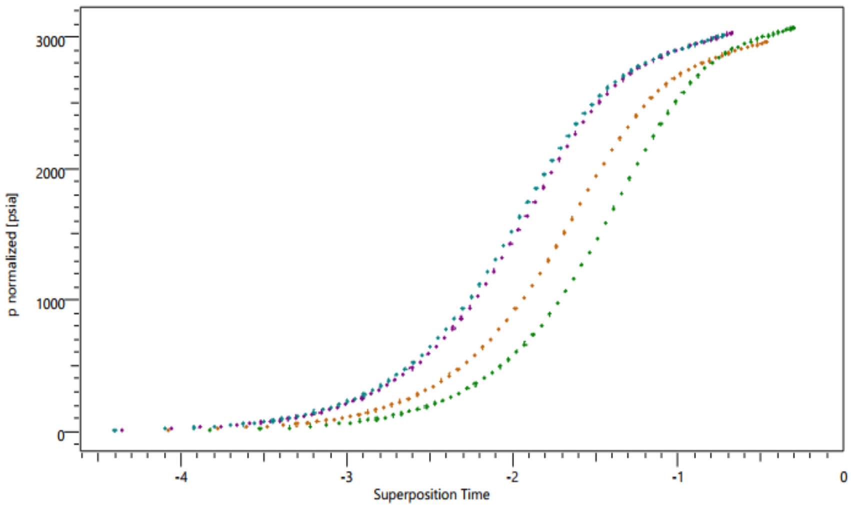

Figure 5. Rate normalized superposition plot

Using conventional well test interpretation techniques, a qualitative view of any build-up in Fig.3 shows only two flow regimes, infinite acting radial flow which is characterized by a horizontal line on the pressure derivative plot and wellbore dominated flow which is characterized by a unit slope on both log-log plots. This might lead us to believe that the reservoir is infinite acting, whereas history matching the data Fig.6, Fig.7 and Fig.8 show otherwise. Fig.6 shows that although the infinite acting model fits the early and middle time data, it does not fit the late time buildup data of the log-log diagnostic plot of the selected buildup.

Figure 7 shows that the model does not match the late time buildup of the history plot. From the superposition plot shown in Fig 8 it is seen that like the diagonostic plot, the model only matches the early and middle time data but does not match the late time data on the superposition plot. In other words, the infinite acting radial model does not match the test data and the data is affected by boundary effects. However, selecting a model with a boundary based on the given test data may result in the reservoir engineer selecting several possible models to see which best matches the data. This is where the use of deconvolution may prove advantageous already as the system was chosen carefully to be a linear system.

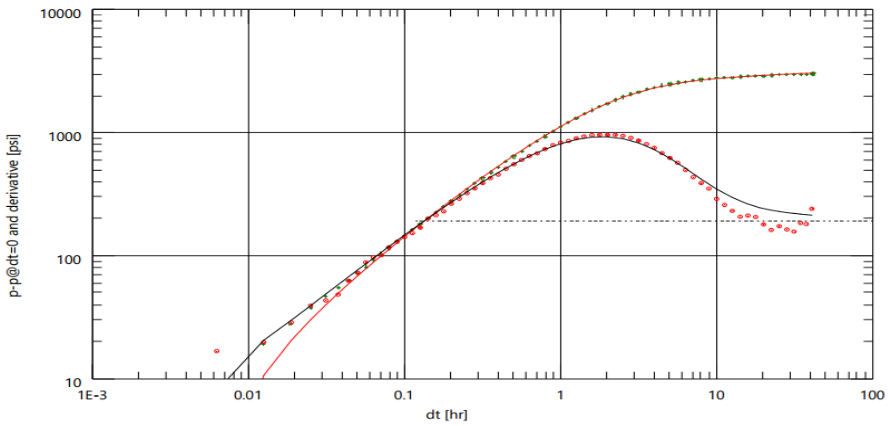

Figure 6. log-log diagonostic plot of noisy data showing model match

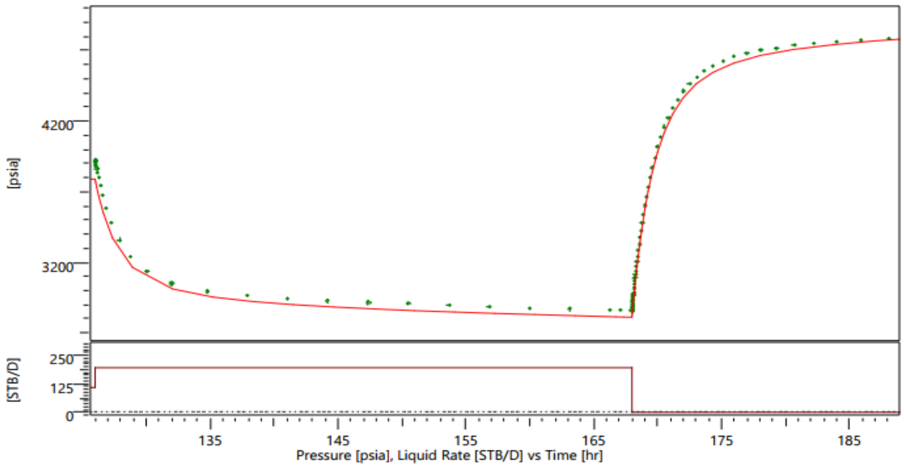

Figure 7. Zoom on History plot showing model match of noisy data

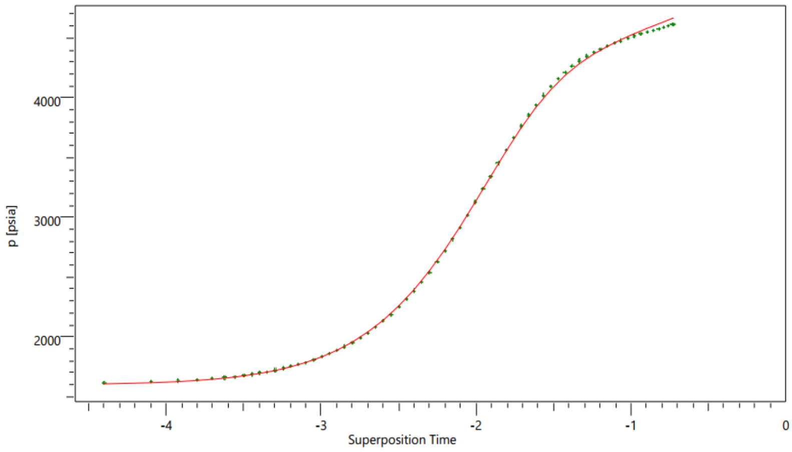

Figure 8. Superposition plot showing model match of noisy data

Figure 9 shows the log-log diagnostic plot of the deconvolve response. From this plot it is seen that for about 50 hours there exist a boundary dominated flow regime which is most likely due to the presence of a sealing fault effectively narrowing down the list of possible boundary models. Hence it can be said that deconvolution increases the amount of information that can be analyzed with pre-existing methods.

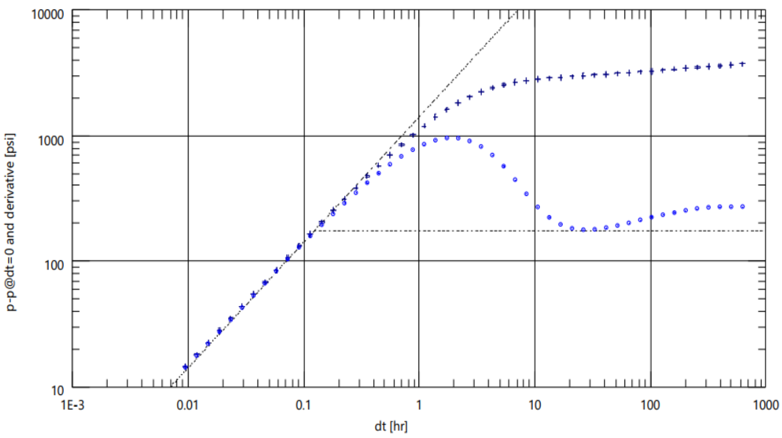

Figure 9. Log-Log diagnostic plot of deconvolve noisy data.

The superposition plot for the deconvolve response shown in Fig 10 does not resemble that of a buildup, instead it resembles that of a drawdown this is because the deconvolution process produces a constant rate pressure response.

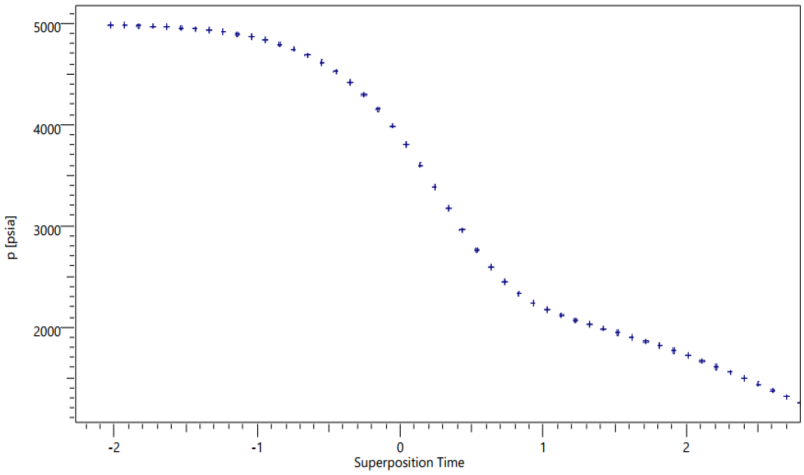

Figure 10. Superposition plot of the deconvolve response

The model match of the deconvolve data on the superposition and log-log diagnostic plots is shown in Fig.11 and Fig.12 respectively while Fig.13 is the history plot showing the deconvolve pressure (black), the deconvolve rate (red) and observed pressure response model match (green). The model match in Fig.11 and Fig.12 are acceptable. While the model in Fig.13 matches all the buildups perfectly but does not produce a perfect match on the drawdown data. This may be attributed to the fact that deconvolution is carried out on the whole rate history using pressure data from only the four buildups.

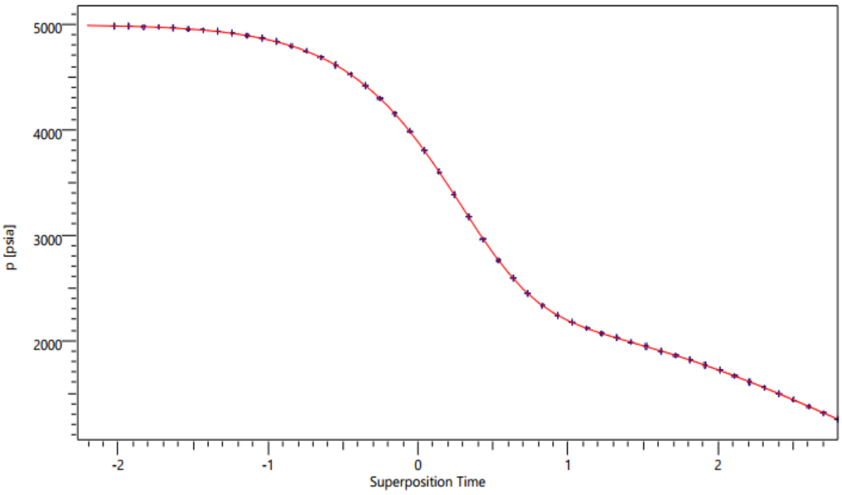

Figure 11. Superposition plot of the deconvolve data showing model match

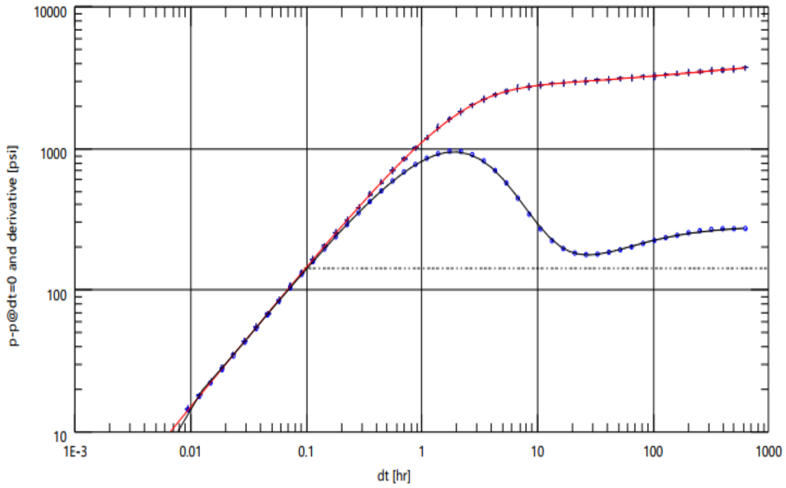

Figure 12. Log-Log diagnostic plot of the deconvolve data showing model match

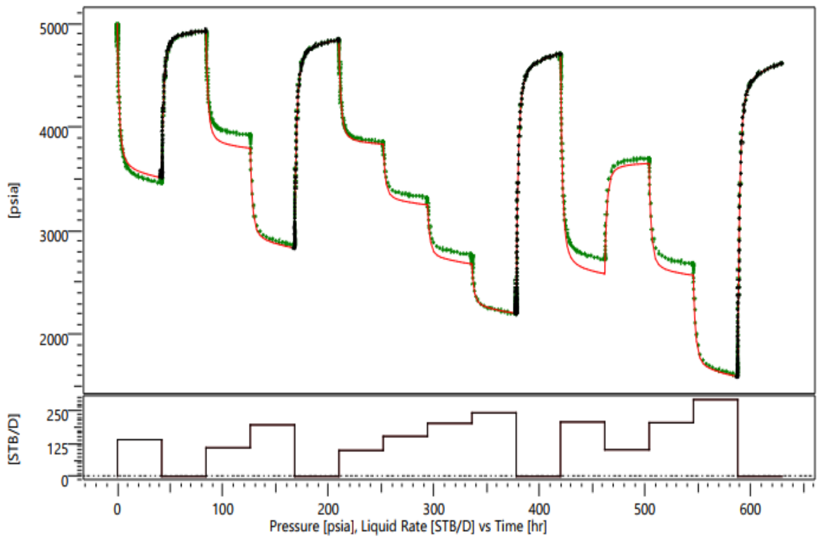

Figure 13. History plot showing the deconvolve pressure (black), the deconvolve rate (red) and the observed pressure response (green)

Table 4 shows the percentage deviation between deconvolve model match values and actual values. From the table it is seen that the deviations are within acceptable engineering limits.

Table 4. Comparison between model match values and actual values.

Parameter	**Model match value**	**Actual value**	**% Deviation**
Skin	3.23	3	7.7
Flow capacity (Kh)	396	400	-1.0
Wellbore storage coefficient	0.00972	0.01	-2.8
Initial reservoir pressure	4996.9	5000	-0.062
Distance to fault	409	400	2.25

4. Conclusion

A demonstration of the use of non-linear deconvolution in analyzing relatively short variable rate well test data has been carried out using sapphire's test design module and python programming language. The results show as indicated by the log-log diagnostic plot that deconvolution avails more data for selecting an interpretation model.

Deconvolution carried out on the simulated data indicated the presence of a sealing fault boundary model unidentifiable with conventional techniques. Similarly, based on the deconvolve data the following parameters were estimated; skin (3.28), wellbore storage coefficient (0.00972 bbl/psi), flow capacity (396 md.ft), initial reservoir pressure (4996.9 psi) and distance to fault boundaries (409 ft). The deviations between these model match parameters and actual reservoir parameters used in simulation was shown to have an absolute value less than 8%.

References

[1] S. Chapra, R. Canale, *Numerical methods for engineers*, 6th ed., Boston: McGraw-Hill, 2006, pp 78 – 104.

[2] L. Dake, *Practice of Reservoir Engineering*, 1st ed., Amsterdam: Elsevier Science, 1994, pp 147-154.

[3] A. Gringarten, "From Straight Lines to Deconvolution: The Evolution of the State of the Art in Well Test Analysis" SPE Reservoir Evaluation & Engineering Journal, vol. 11, pp 41-62, 2008.

[4] O. Houze, E. Tauzin, O. Allain, "New Methods to deconvolve Well-Test Data under Changing Well Conditions", SPE Annual Technical Conference and Exhibition, Florence, pp. 20-22 September 2010.

[5] F. Kuchuk, M. Onur, F. Hollaender, *Pressure transient formation and well testing*, 11th ed., Amsterdam: Elsevier, 2010, pp 76 – 77.

[6] M. Levitan, "Practical Application of Pressure-Rate Deconvolution to Analysis of Real Well Tests", SPE Reservoir Evaluation & Engineering Journal, vol. 8, pp 113-121, 2005.

[7] M. Levitan, G. Crawford, A. Hardwick, "Practical Considerations for Pressure-Rate Deconvolution of Well Test Data", SPE Reservoir Evaluation & Engineering Journal, vol. 11, pp 35-47, 2006.

[8] T. Von Schroeter, F. Hollaender, A. Gringarten, "Deconvolution of Well Test Data as a Nonlinear Total Least Squares Problem", SPE Annual Technical Conference and Exhibition, New Orleans, p 30 September – 3 October 2001.

[9] T. Von Schroeter, F. Hollaender, A. Gringarten, "Deconvolution of Well Test Data as a Nonlinear Total Least Squares Problem", SPE Reservoir Evaluation and Engineering Journal, vol. 9, pp 375 - 390, 2004.