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Automated Well Test Analysis II Using 'Well Test Auto'

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Abstract
The use of computers in the petroleum industry is both cost effective and a solution to human errors in carrying out data analysis. In well testing, recent advances in gauge equipments and the need for a timely interpretation of well-test data, to mention a few, have spurred the need for a computer aided approach.
The well test interpretation procedure has been completely automated in this work by implementing the approach presented in part I of this paper, in a computer program using Visual Basic Excel; WELL TEST AUTO. This program was tested on ten (10) data sets. These data sets comprise of eight (8) design/simulated data sets (Using a simulator and lifted from literature) and two (2) actual field data sets (lifted from literature). Although the results of the ten (10) data sets proved successful as the confidence intervals (CIs) of the parameters were within an acceptable range, selected three (3) data sets were analyzed and presented in this work.

1.0 Introduction

In automated type-curve matching, the selection of an appropriate reservoir model and the initial parameter estimation are crucial for obtaining accurate results. The selection of invalid or wrong reservoir models is usually encountered in the conventional and type-curve method. This is due to the subjectivity of these methods and the compounding problem of noise in the pressure transient data. Secondly, there are limited type-curves available for matching the diverse reservoir configurations.
Also wrong initial estimate of regression parameters can result in wrong results since the regression algorithm might fail to converge to the right results when the initial parameter estimates are far from the actual value. This is as a result of the convergence of some algorithms on local minimum, such as Levenberg–Marquardt's algorithm (**Marquardt, 1963**).
These problems are resolved by computerizing the model selection and initial parameter estimation, since the subjectivity of most test interpretations has been a major cause of these wrong results. Also, quantitative methods such as Confidence Interval and F-test can be used to verify if the selected model is appropriate.

TABLE 1.0: ACCEPTABLE CONFIDENCE LIMITS (Horne, 1995)

Parameter	% Interval	Absolute Interval
K	10	-
C_s	10	-
ω	20	-
λ	20	-
r_e	10	-
S	-	1.0

The aim of this work is to present the results of a new technique/method for automating well test analysis presented in part 1 of this work. This technique is tailored to improve both the performance and accuracy of well test interpretation/analysis and implemented in a computer program, written in Visual Basic programming language. The artificial intelligence (AI) approach used in this project is based on the works of Allain and Horne (1990) and is limited to eight (8) fundamental reservoir models (Anraku and Horne, 1993) are used. Namely; Infinite Acting, Sealing Fault, No flow Outer Boundary, Constant Pressure Outer Boundary, Dual Porosity with Pseudosteady State Interporosity Flow, Dual Porosity with Pseudosteady State Interporosity Flow and Sealing Fault, Dual Porosity with Pseudosteady State Interporosity Flow and No Flow Outer Boundary and Dual Porosity with Pseudosteady State Interporosity Flow and Constant Pressure Outer Boundary.

1.2 Previous Works

In the 1990s, the use of nonlinear regression became a standard industry practice, with many publications from both the academia and the industry. This led to the specialized development of pressure transient analysis programs by software companies. However, after the technique had become established in engineering practice, the interest in developing further new approaches to nonlinear regression seems to have waned since the late 1990s.
Allain and Horne (1990) used syntactic pattern recognition and a rule-based system to identify the reservoir model by extracting symbolic data from the pressure derivative data. The well and reservoir parameters were also estimated. The limitations of this approach are that it requires a preprocessing of the derivative data in order to distinguish the true response from the noise and a complex definition of rules to accommodate 'nonideal'

behavior.

Anraku and ***Horne*** (***1993***) introduced a new approach to discriminate between reservoir models using the *sequential predictive probability* method. This approach was effective in identifying the correct reservoir models by matching to all candidate reservoir models and then computing the probability (joint probability) that each match would correctly predict the pressure response. Candidate reservoir models and initial estimates of the models' parameters need to be determined in advance for this process.

Athichanagorn and ***Horne*** (***1995***) investigated the use of the artificial neural network and the sequential predictive probability approach to recognize characteristic components of candidate models on the derivative plot (unit slope, hump, at slope, dip, and descending shape). This approach was able to discriminate between candidate reservoir models by identifying the flow regimes corresponding to these characteristic components and make initial estimates of their underlying parameters. Nonlinear regression was simultaneously performed on these parameters to compute best estimates of reservoir parameters.

Bariş et al. (***2001***) demonstrated an approach based on Genetic Algorithm (***GA***) with simultaneous regression to automate the entire well test interpretation process. This was able to select the most probable reservoir model among a set of candidate models, consistent with a given set of pressure transient data. They defined the type of reservoir model to be used as a variable type which was estimated together with the other unknown model parameters (permeability, skin, etc.).

The need for an approach to completely automate the well test interpretation approach can never be over emphasized. The approach presented in this work is the use of Artificial intelligence to select the reservoir model and subsequently estimate the reservoir parameters. The artificial intelligence (***AI***) approach used in this project is based on the works of ***Allain*** and ***Horne*** (***1990***); with some modifications. This will involve extracting a symbolic representation of the reservoir model from the pressure transient data, estimation of the model parameters from the characteristic flow regimes and subsequently, performing nonlinear regression to refine these parameters.

2.0 Program Description

The methodology of this project was implemented by developing a computer program named '***WELL TEST AUTO'***. This program was developed using Visual Basic for Applications (VBA) Excel. This program completely automates the model selection and parameter estimation of single vertical oil wells for single layered reservoirs. The program is divided into six (***6***) sheets, as follows;

1. '***Welcome***' sheet: This sheet is basically a welcome splash screen showing basic instructions on how to use the program.
2. '***Data Input***' sheet: This sheet allows the user to load pressure-time data from a text file and to input the well and reservoir parameters.
3. '***Plots***' sheet: On this sheet, users can view the different diagnostic plots such as, the log-log plot, semi-log MDH plot, Horner's plot and the Cartesian plot.
4. '***Model Selection***' sheet: This sheet performs the model selection and initial parameter estimation.
5. '***Analysis and Results***' sheet: On this sheet, the initial estimates for the selected model are shown and used to perform non-linear regression. There are also options available for manually selecting a regression model and for inputting initial regression parameters.
6. '***Match Plot***' sheet: The result of the math is viewed graphically on this sheet. Also a manual match can be performed on this sheet.

3.0 Result Analysis

The results of the application of WELL TEST AUTO to simulated and actual well test data are presented here. Although the program was tested with ten (10) data sets; two (2) of which are actual data sets, while the remaining eight (8) are simulated data from literature and with PanSystem ^{TM}, this work presents the results of three (3) selected data sets from the ten (10) used to test the program.

1.0 Test 1

This is a simulated drawdown test data taken from ***Onyekonwu*** (***1997***). This is an infinite acting homogenous reservoir model. The program, '*WELL TEST AUTO*', correctly chose the reservoir model and made reasonably acceptable estimates of the reservoir parameters.

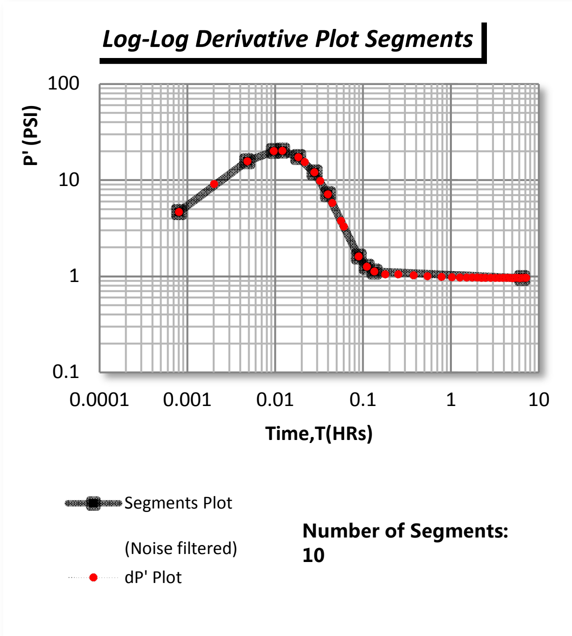

FIGURE 3.1.1: LOG-LOG DERIVATIVE SEGMENTS PLOT FOR DATA SET 1

The program obtained ten (10) segment objects from the pressure derivative plot (See FIGURE 3.1.1 and TABLE 3.1.1). From this segment collection, no MINIMA were found and the last segment feature is a STRAIGHT_SECTION_FLAT.

The semi-log plot and the log-log pressure drop plot are segmented into five (5) and seven (7) segments respectively (see TABLE 3.1.2 and TABLE 3.1.3).

With these, the program matched segment 10 (STRAIGHT_SECTION_FLAT) of the pressure derivative log-log plot with the semi-log segments (see TABLE 3.1.2). It chose segment 5 (STRAIGHT_SECTION_DOWNTURN) of the semi-log plot as the straight line from which the initial estimates of permeability, K_{est}, Skin, S_{est} were obtained. Also, the wellbore storage constant, $C_{s,est}$ is obtained from the first unit slope (approximate), segment 1 (STEP) on the log-log pressure drop segments (see TABLE 3.1.3). These initial estimates were regressed on the *infinite acting model*, using the first cycle of data points and the refined estimates used to generate the *dimensionless pressure derivative plot* shown in FIGURE 3.1.2. From this plot, it can be seen that segment 10 (STRAIGHT_SECTION_FLAT) of the pressure derivative log-log plot falls on 0.5. The program suggested the *infinite acting model*.

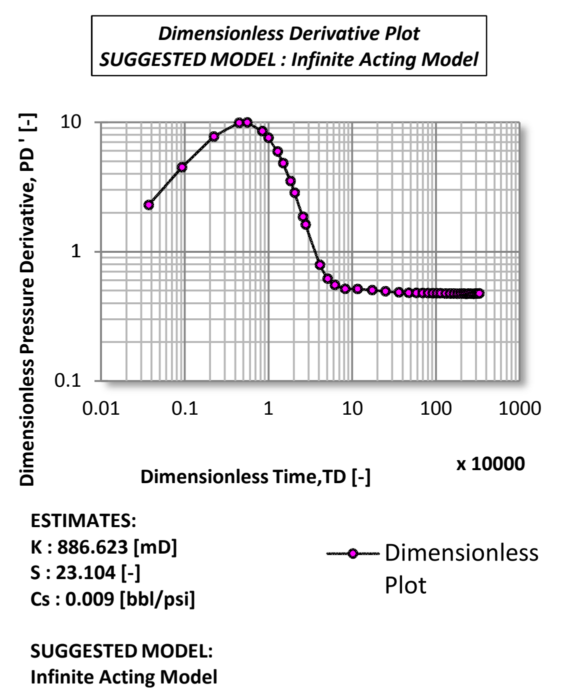

FIGURE 3.1.2: DIMENSIONLESS DERIVATIVE PLOT OF TEST 1

These estimates (k_{est}, S_{est} and C_{est}) were regressed on using the suggested model and the result is presented graphically in FIGURE 3.1.3 and also in TABLE 3.1.4.

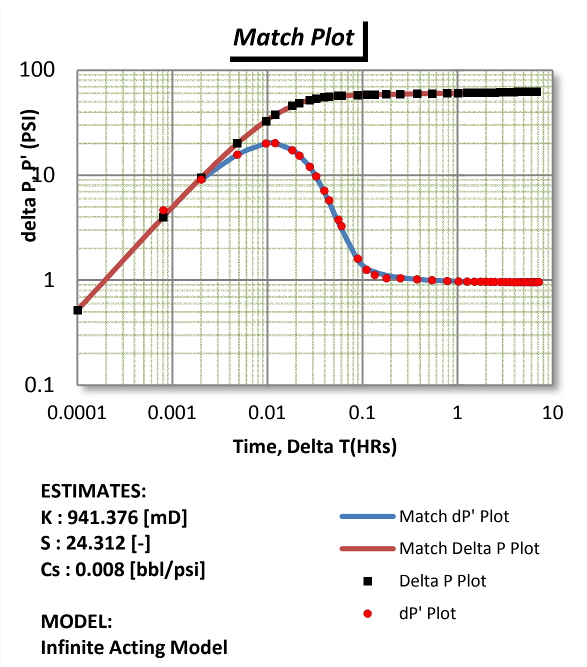

FIGURE 3.1.3: MATCH RESULT OF TEST 1

From FIGURE 3.1.3, the result is a good match and comparing the confidence intervals of the regression estimates in TABLE 3.1.4 with TABLE 1.0, the results are acceptable.

2.0 Test 2

This is an actual buildup test data taken from ***Horne*** (*1995*). The pressure data and the values of the well and reservoir properties are presented in appendix *A-2*. This is an infinite acting homogenous reservoir model. The program, ‘WELL TEST AUTO’, was able to correctly choose the right model and make reasonably acceptable estimates of the reservoir parameters. This was achieved despite the late time noise in the pressure derivative data.

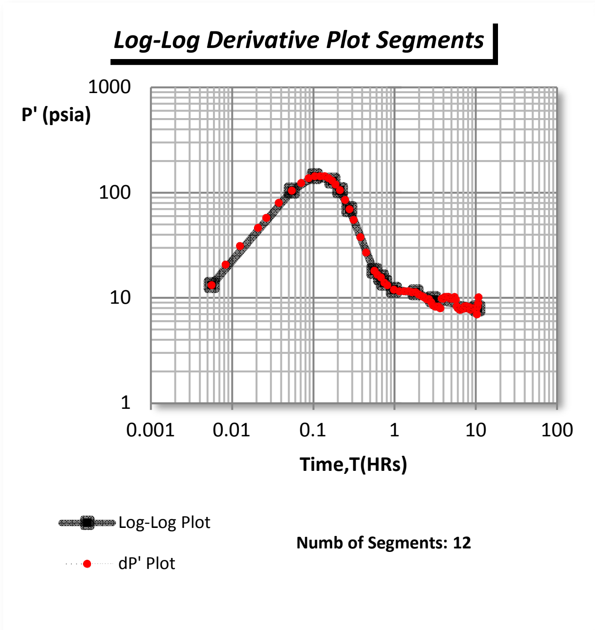

FIGURE 3.1.4: DATA SET 2 LOG-LOG DERIVATIVE SEGMENTS

The program obtained twelve (12) segment objects from the pressure derivative plot (See FIGURE 3.1.4 and TABLE 3.1.5). From this segment collection, no MINIMA were found and the last segment feature is a STEP_FLAT. This last feature seems to bound only a point; this is due to the redundant data points and outliers cut off while smoothening the log-log derivative plot.

The semi-log plot and the log-log pressure drop plot are both segmented into seven (7) segments (see TABLE 3.1.6 and TABLE 3.1.7).

With these, the program matched segment 12 (STEP_FLAT) of the pressure derivative log-log plot with the semi-log segments (see TABLE 3.1.6), from which it chose segment 7 (STRAIGHT_SECTION_UPTURN) as the straight line from which initial estimates of permeability, K_{est}, Skin, S_{est} were obtained. Also, the wellbore storage constant, $C_{s,est}$ is obtained from the first unit slope (approximate) segment (STEP) on the log-log pressure drop segments (see TABLE 3.1.7). These initial estimates were regressed on the *infinite acting model* using the first cycle of data points and the refined estimates used to generate the *dimensionless pressure derivative plot* shown in FIGURE 3.1.5. From this plot, it can be seen that segment 12 (STEP_FLAT) of the pressure derivative log-log plot falls on 0.5. The program suggested the *infinite acting model*.

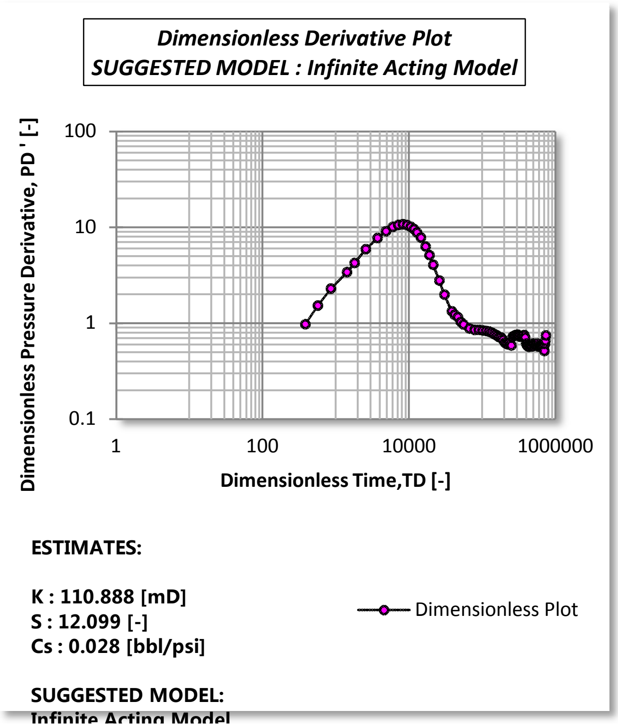

FIGURE 3.1.5: DIMENSIONLESS DERIVATIVE PLOT OF TEST 2

These estimates (k_{est}, S_{est} and C_{est}) were regressed on using the suggested model and the result is presented graphically in FIGURE 3.1.6 and also tabulated in TABLE 3.1.8.

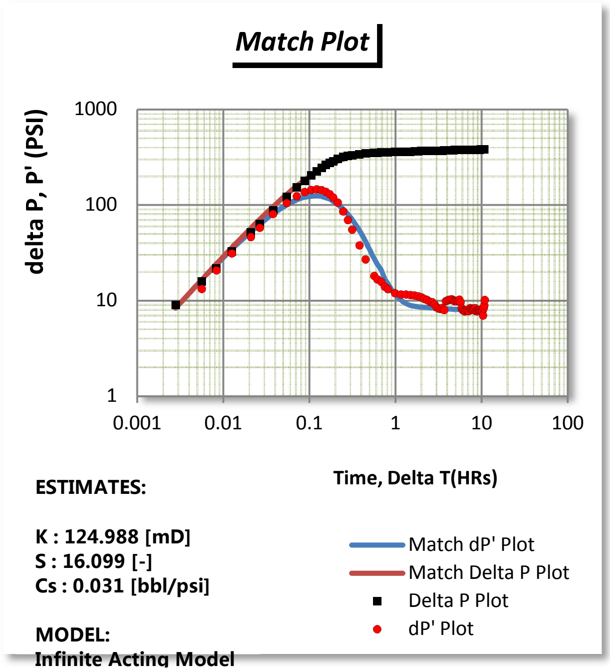

FIGURE 3.1.6: MATCH RESULT OF TEST 2

Form FIGURE 3.1.6, the result is a good match and comparing TABLE 3.1.8 with TABLE 1.0, the confidence intervals of the results are acceptable.

3.0 Test 3

This is a drawdown test and the data set was simulated using ***PanSystem*** ^{TM}. This is a dual porosity with a constant pressure outer boundary reservoir model. From FIGURE 3.2.7, the program was able to extract a symbolic representation of the reservoir model from the pressure derivative plot. The extracted features are tabulated in TABLE 3.2.9.

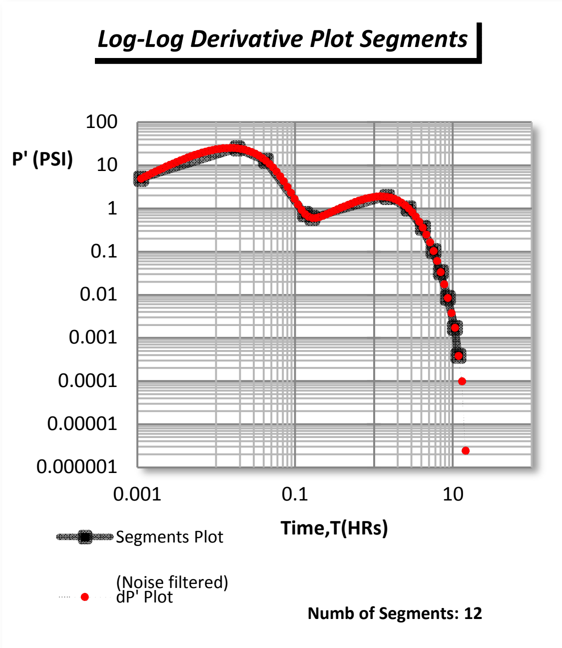

FIGURE 3.1.7: DATA SET 3 LOG-LOG DERIVATIVE SEGMENTS

Twelve (12) segment objects were obtained from the pressure derivative plot. From these segments the three (3) sections; section 3 (INFLEXION_DOWN), section 4 (MINIMA) and section 5 (INFLEXION_UP) were matched with the segment collection of the semi-log plot. Since all three (3) segments match in time with segment 5 (STRAIGHT_SECTION_DOWNTURN) of the semi-log plot, only a single set of initial estimates of permeability, K_{est}, Skin, S_{est} were obtained; else, different sets of K_{est} and S_{est} would have been estimated and with the first 1.5 cycle of data points regressed on the infinite acting model to select the best set (based on the least sum of squares). Also the wellbore storage constant, $C_{s,est}$ is obtained from the unit slope segment on the log-log pressure drop segment. This refined initial estimate of permeability, K_{est} was used to generate dimensionless pressure derivative plot. Comparing the dimensionless pressure derivative plot (FIGURE 3.1.8), with the segmented pressure derivative data, the lowest point on the MINIMA falls below 0.5 and this indicated a dual porosity. From this minimum point, dual porosity parameters (ω_{est} and λ_{est}) were estimated. Also, a STEP_DOWNTURN at the end of the pressure derivative curve suggested the constant pressure outer boundary; hence the distance to boundary, $r_{e,est}$ was calculated using Equation 3.5.16. The program suggested a *dual porosity with constant pressure outer boundary model*.

The semi-log plot and the log-log pressure drop plot are segmented into five (5) and six (6) segments respectively (see TABLE 3.1.10 and TABLE 3.1.11).

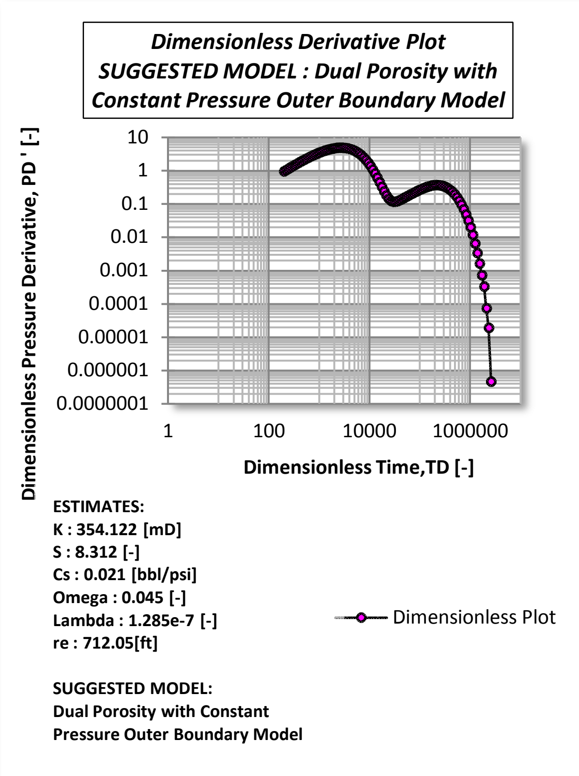

FIGURE 3.1.8: DIMENSIONLESS DERIVATIVE PLOT OF TEST 3

Nonlinear regression was performed on the suggested model (*Dual porosity with Constant Pressure Outer Boundary Model)* with the initial parameter estimates (k_{est}, S_{est} , C_{est}, ω_{est}, λ_{est} and $r_{e,est}$), to obtain refined parameter estimates and the result is presented graphically in FIGURE 3.1.9 and also tabulated in TABLE 3.1.12.

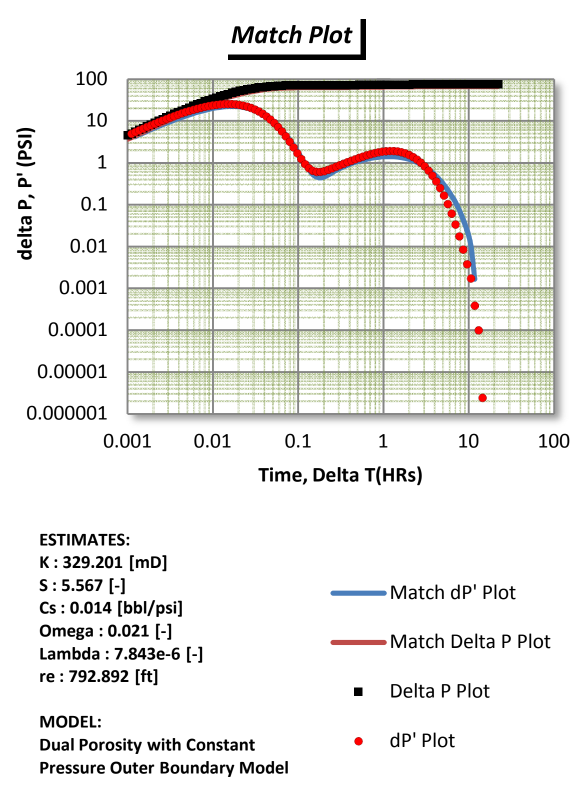

FIGURE 3.1.9: MATCH RESULT OF TEST 3

The regression result shows a good match can be seen in FIGURE 3.1.9. Also, comparing TABLE 3.1.12 with

TABLE 1.0, the confidence intervals of the results are acceptable.

Conclusions

This work is limited to a single vertical oil well, single layer, as the primary objective of this work is to demonstrate and present the merits of computerizing well test analysis. Although the intervention of a well test analyst is required, this can be greatly minimized by incorporating more complex models, to account for the diverse reservoir configurations, into the program.

The well test interpretation procedure has been completely automated in this work for eight fundamental reservoir models (*Anraku*, *1993*). The following conclusions were drawn from the findings of this work;

1. The computer program, *WELL TEST AUTO*, developed for this project, although with limited number of reservoir models, has proved to be a good aid for automating well test interpretation.
2. The selected three (*3*) data sets analyzed and presented in this work showed acceptable results as the confidence intervals (*CIs*) of the parameters were within the acceptable ranges.
3. The *pre-segmentation* and *post-segmentation* smoothening algorithm presented in part 1 of this paper proved helpful in handling noisy data as can be seen in the results of *Test 2*. This was able to extract a well defined symbolic data.
4. The segmented dimensionless pressure derivative curve provides a more elaborate means of discriminating the reservoir models. This is so, as the curve depicts a unified signature for different flow regimes.
5. The Levenberg-Marquardt (Marquardt, *1963*), nonlinear regression algorithm with *the barrier method* helped to avoid inconsistency or stability issues with the analytical reservoir models used. Also, the objective function was weighted with the sum-of-squares of the pressure derivative and this improved convergence.
6. This method has proved to be a time and cost effective way of carrying out well test interpretation as it required relatively minimal computational time and hardware.

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TABLE 3.1.1: LOG-LOG DERIVATIVE SEGMENT ATTRIBUTES FOR DATA SET 1

	Xn	*Yn*	*No. Of Points Bound*	*Slope*	*Feature*
0	0.0008	4.646088	2	0.677223801	STEP
1	0.0048	15.66903	2	0.677223801	STEP
2	0.0096	20.03112	1	0.354327558	STEP_UP
3	0.012	20.17195	1	0.031396723	STEP
4	0.0182	17.27141	1	-0.372712906	MAXIMA
5	0.0278	12.02882	2	-0.82725437	STEP_DOWN
6	0.0396	7.109825	2	-1.47135447	STEP_DOWN
7	0.0888	1.601583	4	-1.849089183	INFLEXION_DOWN
8	0.11	1.252701	1	-1.147583128	STEP_DOWN
9	0.134	1.119942	1	-0.56762146	STEP_DOWN
10	6.42	0.960532	23	-0.02287829	STRAIGHT_SECTION_FLAT

TABLE 3.1.2: SEMI-LOG DERIVATIVE SEGMENT ATTRIBUTES FOR DATA SET 1

	Xn	*Yn*	*No. Of Points Bound*	*Slope*	*Feature*
0	0.0001	3183.245	2	-8.785898548	STEP
1	0.002	3174.302	2	-8.785898548	STEP
2	0.0048	3163.727	1	-27.81348587	STEP_DOWN
3	0.0216	3135.356	4	-43.21756667	INFLEXION_DOWN
4	0.0396	3128.53	3	-25.30505096	STEP_DOWN
5	6.06	3121.438	28	-3.295877382	STRAIGHT_SECTION_DOWNTURN

TABLE 3.1.3: LOG-LOG PRESSURE DROP SEGMENT ATTRIBUTES FOR DATA SET 1

	Xn	*Yn*	*No. Of Points Bound*	*Slope*	*Feature*
0	0.0001	0.518	2	0.960880298	STEP
1	0.002	9.461	2	0.960880298	STEP
2	0.0048	20.036	1	0.857086653	STEP_UP
3	0.0096	32.867	1	0.714045261	STEP_UP
4	0.012	37.446	1	0.584515123	STEP_UP
5	0.0182	45.577	1	0.47177973	STEP_UP
6	0.0278	51.924	2	0.314835577	STEP_UP
7	6.06	62.325	30	0.034546937	STRAIGHT_SECTION_FLAT

TABLE 3.1.4: MATCH RESULT OF TEST 1

Suggested Model	***Infinite Acting Model***					
Number of Iteration:	**16**					
Data Length:	**45**					
Parameters	***Initial Estimates***	***Regression Estimates***		***95% CI***	***CI [%]***	***Actual Values***
Permeability, K:	**886.623**	**941.378**	[mD]	**9.89**	**1.05**	**933.00**
Skin, S:	**23.1042**	**24.312**	[-]	**3.31E-01**	**-**	**25.00**
Wellbore Storage Constant, Cs:	**9.49E-03**	**8.89E-03**	[bbl/psi]	**2.35E-05**	**0.276**	**9.00 E-03**

TABLE 3.1.5: LOG-LOG DERIVATIVE SEGMENT ATTRIBUTES FOR DATA SET 2

	Xn	*Yn*	*No. Of Points Bound*	*Slope*	*Feature*
0	0.0056	13.20161	6	0.917681645	STEP
1	0.0542	104.6135	6	0.917681645	STEP
2	0.1042	143.2516	3	0.45672306	STEP
3	0.1708	129.6996	2	-0.201103286	MAXIMA
4	0.2125	105.5989	2	-0.933208081	STEP_DOWN
5	0.2782	69.48921	2	-1.561823615	STEP_DOWN
6	0.5625	18.043	4	-1.940052789	INFLEXION_DOWN
7	0.6792	15.66116	1	-0.750957354	INFLEXION_DOWN
8	0.7458	13.93238	1	-1.250436784	INFLEXION_DOWN
9	0.9792	11.92589	2	-0.599271463	STEP_DOWN
10	1.8125	11.27371	5	-0.085580688	INFLEXION_FLAT
11	2.9792	9.712065	4	-0.300040411	INFLEXION_DOWN
12	10.4792	7.946413	1	-0.050831143	STEP_FLAT

TABLE 3.1.6: SEMI-LOG PRESSURE SEGMENT ATTRIBUTES FOR DATA SET 2

	Xn	*Yn*	*No. Of Points Bound*	*Slope*	*Feature*
0	0.0028	1824.36	4	50.82538681	STEP
1	0.0208	1866.76	4	50.82538681	STEP
2	0.0375	1902.68	2	136.5048277	STEP_UP
3	0.0708	1967.12	2	237.1790092	STEP_UP
4	0.1875	2103.19	7	321.3190249	INFLEXION_UP
5	0.2458	2131.69	2	243.8629923	STEP_UP
6	0.3125	2147.97	2	155.4748046	STEP_UP
7	10.3125	2196.12	64	24.1885255	STRAIGHT_SECTION_UPTURN

TABLE 3.1.7: LOG-LOG PRESSURE DROP SEGMENT ATTRIBUTES FOR DATA SET 2

	Xn	*Yn*	*No. Of Points Bound*	*Slope*	*Feature*
0	0.0028	8.99	2	0.813261424	STEP
1	0.0083	21.81	2	0.813261424	STEP
2	0.0708	151.75	6	0.899900906	INFLEXION_UP
3	0.1208	226.37	3	0.741687219	STEP_UP
4	0.1708	275.9303	3	0.566481755	STEP_UP
5	0.2125	302.14	2	0.420085097	STEP_UP
6	0.3125	332.6	3	0.243729437	STEP_UP
7	10.3125	380.75	64	0.02865446	STRAIGHT_SECTION_FLAT

TABLE 3.1.8: MATCH RESULT OF TEST 2

Suggested Model	***Infinite Acting Model***					
Number of Iteration:	***28***					
Data Length:	***90***					
Parameters	***Initial Estimates***	***Regression Estimates***		***95% CI***	***CI [%]***	***Actual Values***
Permeability, K:	**110.888**	**124.888**	[mD]	**12.78**	**5.42**	**128.12**
Skin, S:	**12.099**	**16.099**	[-]	**1.87**	**-**	**18.37**
Wellbore Storage Constant, Cs:	**0.028**	**0.036**	[bbl/psi]	**2.82E-03**	**7.83**	**0.041**

TABLE 3.1.9: LOG-LOG DERIVATIVE SEGMENT ATTRIBUTES FOR DATA SET 3

	Xn	*Yn*	*No. Of Points Bound*	*Slope*	*Feature*
0	0.00111	4.902302	27	0.575259199	STRAIGHT_SECTION
1	0.018461	24.70142	27	0.575259199	STRAIGHT_SECTION
2	0.042466	12.73834	8	-0.794976716	MAXIMA
3	0.133506	0.739509	11	-2.48496869	INFLEXION_DOWN
4	0.164418	0.601398	2	-0.992625979	MINIMA
5	1.464338	1.852286	21	0.514425389	INFLEXION_UP
6	2.735155	1.00077	6	-0.985380484	MAXIMA
7	4.148354	0.35663	4	-2.477231305	STEP_DOWN
8	5.669518	0.102849	3	-3.980373447	STEP_DOWN
9	6.982211	0.033338	2	-5.409382858	STEP_DOWN
10	8.59884	0.008384	2	-6.628235079	STEP_DOWN
11	10.58978	0.001709	2	-7.635355512	STEP_DOWN
12	11.75196	0.000382	1	-14.39701237	STEP_DOWNTURN

TABLE 3.1.10: SEMI-LOG PRESSURE SEGMENT ATTRIBUTES FOR DATA SET 3

	Xn	*Yn*	*No. Of Points Bound*	*Slope*	*Feature*
0	0.001	3995.533	11	-17.71555882	STRAIGHT_SECTION
1	0.003144	3986.72	11	-17.71555882	STRAIGHT_SECTION
2	0.006517	3975.318	7	-36.01608794	STEP_DOWN
3	0.031072	3939.099	15	-53.39460918	INFLEXION_DOWN
4	0.047127	3932.951	4	-33.9850482	STEP_DOWN
5	17.82395	3924.656	57	-3.218157735	STRAIGHT_SECTION_DOWNTURN

TABLE 3.1.11: LOG-LOG PRESSURE DROP SEGMENT ATTRIBUTES FOR DATA SET 3

	Xn	*Yn*	*No. Of Points Bound*	*Slope*	*Feature*
0	0.001	4.467382	16	0.9246265	STRAIGHT_SECTION
1	0.005291	20.8479	16	0.9246265	STRAIGHT_SECTION
2	0.010968	36.18905	7	0.756536202	STEP_UP
3	0.018461	49.25301	5	0.591945089	STEP_UP
4	0.031072	60.90089	5	0.407715543	STEP_UP
5	0.058038	68.87549	6	0.196948007	STEP_UP
6	17.82395	75.34431	55	0.015673932	STRAIGHT_SECTION_FLAT

TABLE 3.1.12: MATCH RESULT OF TEST 3

Suggested Model	***Dual Porosity with Constant Pressure Outer Boundary Model***					
Number of Iteration:	**31**					
Data Length:	**101**					
Parameters	***Initial Estimates***	***Regression Estimates***		***95% CI***	***CI [%]***	***Actual Values***
Permeability, K:	**354.122**	**329.201**	[mD]	**9.99**	**3.04**	**340.0**
Skin, S:	**8.312**	**5.567**	[-]	**0.35**	**-**	**5.0**
Wellbore Storage Constant, Cs:	**0.0212**	**0.014**	[bbl/psi]	**1.71E-3**	**12.2**	**0.01**
Omega, ω:	**0.0452**	**0.021**	[-]	**0.004**	**19.04**	**0.01**
Lamda, λ:	**1.285E-7**	**7.843E-6**	[-]	**6.021E-7**	**7.68**	**5.00E-7**
Distance to Boundary, re:	**712.015**	**792.892**	[ft]	**52.218**	**6.59**	**800**