White Paper

OptiRamp® Decline Analysis

Optimizing Oil Field Production Rates through Data Analytics

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Introduction

Oil and gas well production has been extensively studied for nearly a century; notably the well-known deliverability equation introduced by Rawlins and Schellhardt in 1935 is still at the core of various control systems. Recent developments in processing and data capture algorithms and hardware allow for more advanced and accurate forecasts, diagnostics, and trend analyses. Statistics & Control, Inc., (S&C) capitalizes on the theory and developments with big data processing and takes the technological leap forward with its *OptiRamp* Oil Field Model. The Oil Field Model displays the multiphase flow in an integrated system of reservoirs, wellbores, well tubing strings, surface pipeline systems, fluid separation units, and other facilities.

The *OptiRamp* Full-Field Model is capable of simulating both reservoirs and gathering systems. This model optimizes the production rate and well connections in response to changing operational conditions. The objective function is the weighted sum of well rates. Physical decision variables include gas rates and well choke that control the production rate of individual wells. Constraints include minimum/maximum flow rates and pressure limits imposed on production wells and/or network nodes as well as the maximum quantity of gas available for groups of gas-lift wells.

This white paper describes three major components of the Oil Field Model: automated well production rate model coefficient tuning, well diagnostics, and trend analysis. *OptiRamp* uses advanced statistical techniques to auto-adjust model coefficients and perform well diagnostics, while the trend analysis is based on the famous Arps equations.

Oil Production Well Simulation Submodule

The *OptiRamp* Oil Production Well Simulation Submodule analyzes data across the entire oil field and produces results for each well. A sample visualization produced by the submodule is shown in Figure 1.

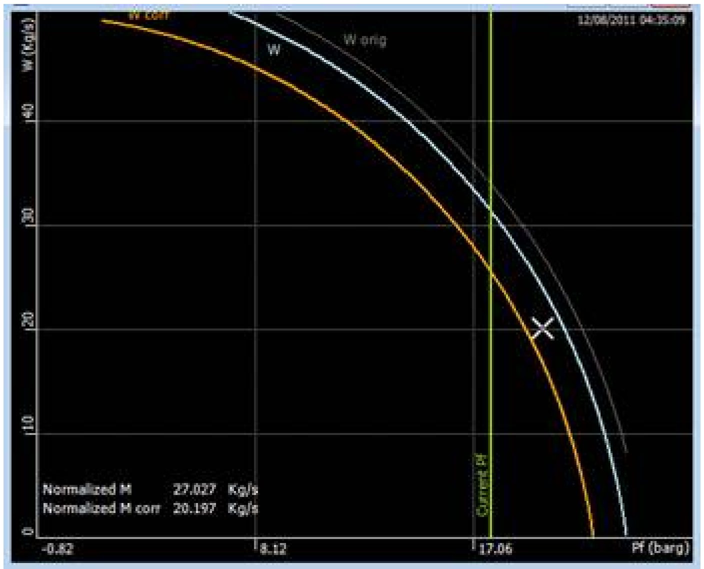

Figure 1. *OptiRamp* oil production well simulation submodule visualization

The *OptiRamp* Oil Production Well Simulation Submodule provides the following functionality:

- Simulates multiphase flow
- Couples with surface facility *OptiRamp* Simulator
- Monitors individual well performance (see Well Diagnostics section)
- Generates deliverability and production forecasts (see Auto-Tuning section)
- Auto-tunes coefficients based on historical and test data (see Auto-Tuning section)
- Calculates current production based on deliverability models
- Calculates current production adjusted to nominal wellhead pressure (displayed as Normalized M in Figure 1)
- Computes reservoir pressure versus time in depletion cases
- Displays initial configured deliverability curve (displayed as gray line in Figure 1)
- Displays deliverability curve auto-tuned based on well test data (displayed as blue line in Figure 1)
- Displays deliverability curve auto-tuned based on real-time data (displayed as orange line in Figure 1)
- Displays current measured/predicted operating point (displayed as white cross in Figure 1)
- Simulates downstream pressure (displayed as vertical green line in Figure 1)
- Provides trend analysis of well performance (see Trend Analysis section)

The *OptiRamp* Oil Production Well Simulation Submodule integrates with the *OptiRamp* Modeling Submodule and the *OptiRamp* Performance Diagnostics Submodule to accomplish these functions (see the corresponding white papers).

Auto-Tuning

OptiRamp models two types of empirical deliverability equations that require auto-tuning. The first type is the standard empirical deliverability equation introduced by Rawlins and Schellhardt in 1935 that relates the well multiphase flow rate with the tubing head pressure, as illustrated in equation (1a). The second type is a slightly modified version of equation (1a), which is given by equation (1b).

$$PI = \frac{W}{\left(P_r^2 - P_f^2\right)^n}, \qquad (1a)$$

$$PI = \frac{W}{P_r - P_f}, \qquad (1b)$$

Where *PI* is the productivity index, *W* is the mass flow rate, P_f is the tubing head pressure, P_r is the reservoir pressure, and *n* is an exponent that accounts for non-steady state flow and, in natural gas cases, for non-ideal gas behaviors. Note that both equations (1a) and (1b) assume the *PI* value is constant and is independent of the flow rate. The rest of this section addresses equation (1a); however, equation (1b) is auto-tuned in a similar manner.

Equation (1a) can be solved for *W* via equation (2).

$$W = PI\left(P_r^2 - P_f^2\right)^n \qquad (2)$$

The coefficients *PI* and *n* are found through log transformation and ordinary least squares regression, which is accomplished by equations (3) and (4).

$$\ln W = \ln PI\left(P_r^2 - P_f^2\right)^n \qquad (3)$$

$$\ln W = \ln PI + n \ln\left(P_r^2 - P_f^2\right) \qquad (4)$$

Equation (4) can be re-written in linear form as equation (5)

$$y = b + nx, \qquad (5)$$

where the intercept *b* and slope *n* are estimated using the ordinary least squares method. *PI* can then be calculated via $PI = e^b$.

Auto-tuning the oil production well deliverability is done in two steps. The first step solves the rate allocation problem, which is described by the Well Test Submodule, while the second step adjusts well deliverability model coefficients based on the Well Test Submodule output. The submodule output is produced via two methods. The first method is a statistical method, where the total flow rate is predicted based on individual oil, water, and gas flow rates. The second method uses actual well test data. In this case, the Well Test Submodule outputs the sum of test oil, test water, and test gas flow rates. Well deliverability model coefficients are then adjusted based on the test pressure and the total test flow rate.

Mathematically, parameter tuning occurs by re-running the ordinary least squares method and by adjusting equation (5) coefficients, thereby introducing equation (6).

$$y = b_{adj} + n_{adj}x \tag{6}$$

This operation, consequently, creates the adjusted deliverability curve. The auto-tuning process continues in real-time as well as off-line (based on well test data) to ensure that the *OptiRamp* Oil Production Well Simulation Submodule is able to fit the curve that is as close as possible to the operating point, ensuring accuracy.

Well Diagnostics

The *OptiRamp* Oil Production Well Simulation Submodule performs a variety of diagnostic activities to ensure each individual well is performing optimally. First, *OptiRamp* uses a Six Sigma approach to measure process variation, or the deviation of a particular metric from its normal or expected value. Given a process variable *x* with a set of historical values x_i, $i = \{1, \dots, m\}$, the operator will be alerted whenever inequality (7) or (8) hold true.

$$x_{i+1} \geq \frac{\sum_{i=1}^{m} x_i}{m} + \delta\sqrt{\frac{\sum_{i=1}^{m}\left(\frac{\sum_{i=1}^{m} x_i}{m} - x_i\right)^2}{m-1}}, \tag{7}$$

$$x_{i+1} \leq \frac{\sum_{i=1}^{m} x_i}{m} - \delta\sqrt{\frac{\sum_{i=1}^{m}\left(\frac{\sum_{i=1}^{m} x_i}{m} - x_i\right)^2}{m-1}}, \tag{8}$$

where δ is a parameter set during commissioning that can be adjusted based on process requirements. For additional details, refer to the Lean Six Sigma Submodule white paper.

The second diagnostic activity is evaluating differences between predicted and measured flow rates. Such deviations may be indicative of structural concerns with the well. *OptiRamp* notifies the operator whenever inequality (9) is satisfied.

$$|W_{Measured} - W_{Predicted}| \geq \gamma, \tag{9}$$

where γ is a parameter set during commissioning that can be adjusted based on process requirements.

The third diagnostic activity covers the entire oil field. There are inherent relationships between clusters of wells that draw oil from the same reservoir. *OptiRamp* measures changes in various corresponding metrics across related wells to ascertain whether certain wells are behaving in a manner similar to the related wells. Again, such observations may be indicative of structural concerns with the well.

The fourth diagnostic activity is to measure deviations in a multiphase flow mix by analyzing the gas-to-oil ratio (GOR) and the water-to-oil ratio (WOR), which in some regions are regulated by the government. Deviations for these two metrics are measured according to equations (7) and (8).

The fifth diagnostic activity is Trend Analysis (see next section), which predicts well depletion.

Trend Analysis

Trend analysis is a procedure for analyzing technological parameter decline rates and forecasting future performance. Flow rate and pressure are two examples of such parameters when it comes to oil field performance monitoring. A curve fit of past parameter performance is done using certain standard curves based on the well-known Arps equations. This curve fit is then extrapolated to predict potential future performance. For extrapolation, it is assumed that the factors causing the historical decline continue unchanged during the forecast period. Trend analysis can be used only when the archived operation history is long enough that a trend can be identified. It is based on measured and computed observations of performance decline.

Arps equations represent the relationship between an efficiency metric, such as a production rate, and time. Let $PV(t)$ be the efficiency metric (could be a measured process variable or a calculated value) at time t. The relationship between the efficiency metric and time is defined according to equation (10).

$$PV(t) = \frac{PV_0}{(1+bDt)^{1/b}}, \tag{10}$$

where PV_0 is the initial efficiency metric value, $b \in [0,1]$ is a constant whose values determine the type of decline, and D is the decline rate. A special case occurs whenever $b = 0$. The decline is called exponential and is described by equation (11).

$$PV(t) = PV_0 e^{-Dt} \tag{11}$$

The decline rate can then be expressed by equation (12).

$$D = -\frac{1}{t} ln \frac{PV(t)}{PV_0} \tag{12}$$

Figure 2 shows an exponential decline for a process variable with actual and fitted values.

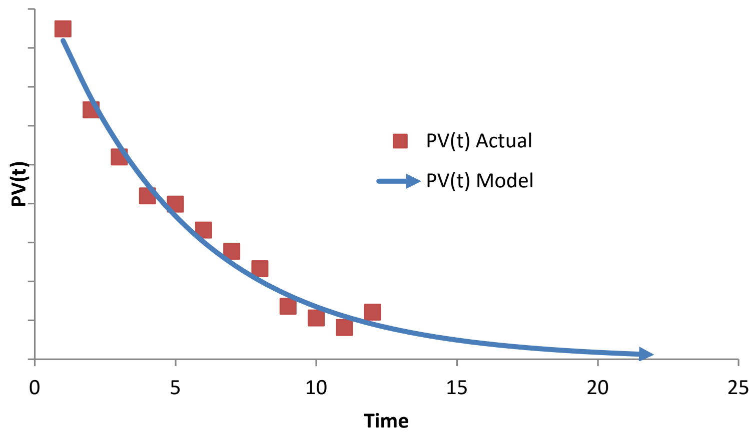

Figure 2. Process variable with exponential decline

When $b = 1$, the decline is called harmonic and is described by equation (13).

$$PV(t) = \frac{PV_0}{1+Dt} \tag{13}$$

The decline rate can then be expressed by equation (14).

$$D = \frac{PV_0 - PV(t)}{PV(t)t} \tag{14}$$

Figure 3 shows an example of harmonic decline.

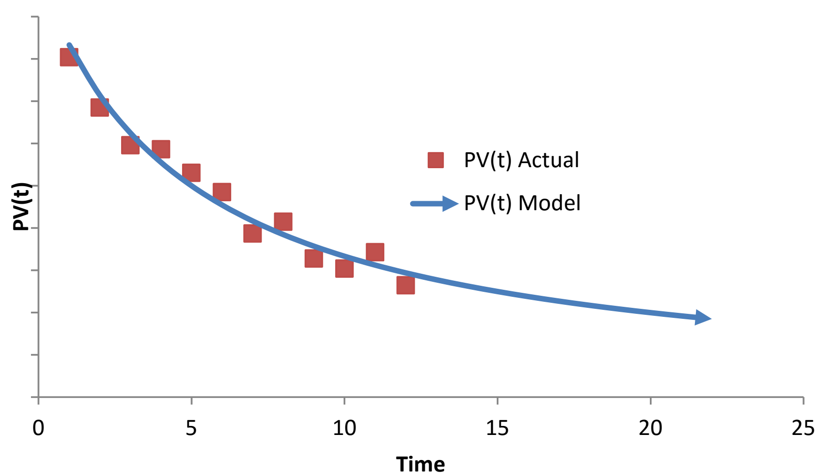

Figure 3. Process variable with harmonic decline

When $b \neq 0,1$, the decline is called hyperbolic and is described by equation (10). The decline rate can then be expressed by equation (15).

$$D = \frac{1-\left(\frac{PV(t)}{PV_0}\right)^b}{\left(\frac{PV(t)}{PV_0}\right)^b bt} \qquad (15)$$

Figure 4 shows an example of hyperbolic decline.

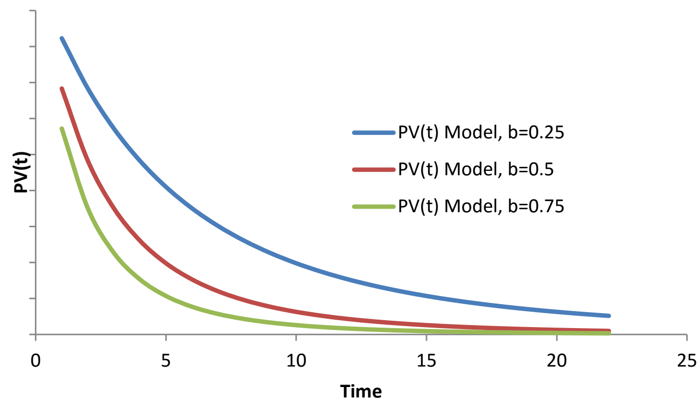

Figure 4. Process variable with hyperbolic decline

In certain cases, *OptiRamp* deploys a modified hyperbolic decline function to limit the overestimated efficiency metric value (especially for longer forecast periods). The modified hyperbolic decline is a weighted sum of the exponential and hyperbolic declines, defined according to equation (16).

$$PV(t) = \alpha \frac{PV_0}{(1+bDt)^{1/b}} + \beta PV_0 e^{-Dt}, \qquad (16)$$

where $\alpha + \beta = 1$.

Figure 5 shows the modeled difference between hyperbolic and modified hyperbolic decline curves where $b = 0.25$.

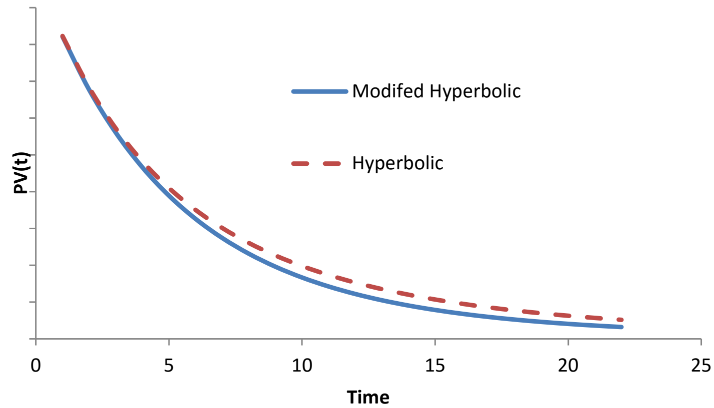

Figure 5. Process variable with hyperbolic decline and modified hyperbolic decline

Regardless of which curve is chosen to represent the process efficiency metric decline, *OptiRamp* uses least squares regression to estimate curve parameters and to generate the line (or curve) of best fit to forecast future performance. These parameters are continuously evaluated as new time intervals are added to the Diagnostics Module historical data.

To estimate coefficients of an exponential decline curve using least squares regression, the exponential equation has to first be translated into a linear equation. To do that, equation (11) is log transformed, as shown in equation (17).

$$\boldsymbol{ln}[PV(t)] = \boldsymbol{ln}[PV_0 e^{-Dt}] \tag{17}$$

Equation (17) translates into equation (18).

$$\boldsymbol{ln}[PV(t)] = \boldsymbol{ln}[PV_0] - Dt \tag{18}$$

Setting $y = \boldsymbol{ln}[PV(t)]$ and $x = t$, logarithmic equation (18) is transformed into the linear equation $y = c - D$. Coefficients c and D are then estimated using ordinary least squares. There should be enough history in a steady state (at least 30 observations) to generate a statistically significant goodness-of-fit. Once coefficients c and D are found, equation (11) is statistically estimated using equation (19).

$$PV(t) = e^c e^{-Dt} = e^{c-Dt} \tag{19}$$

It should be noted that all three decline curves (exponential, harmonic, and hyperbolic) will typically fit the historical data nearly perfectly; however, it's the long-term forecast that is most crucial. Since the exponential decline will show the highest decline, it is considered the most conservative forecast method.

About Statistics & Control, Inc.

S&C—an engineering consulting and technology company headquartered in West Des Moines, IA—solves complex challenges for customers through its unique technology and its highly seasoned team of professionals. The company has a global portfolio spanning the energy, oil and gas, utility, and digital oil field industry sectors. S&C provides clients with turbomachinery control solutions that easily integrate with the existing system as well as *OptiRamp®* solutions, which focus on process and power analytics to optimize processes and, in turn, reduce costs and increase reliability. S&C also provides consulting, dynamic system studies, modeling, automation, training and OTS, and support services.

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