Stochastic Modeling of Oil and Gas Production

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Introduction Montney Wells

- Oil and gas operators in both British Columbia and Alberta are currently pursuing development of the Montney formation.
- It is currently one of the top plays in North America, in terms of number of wells drilled per year, investment dollars spent and overall hydrocarbon production.
- It covers a geographical region of approximately 130,000km, with thickness between 100m-300m.
- Due to its thickness, much of the Montney can supported multiple layers of stack horizontal wells.
- The Montney holds approximately 449 Tcf of marketable natural gas.

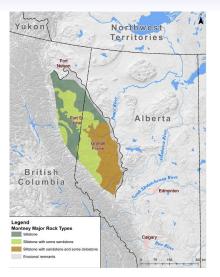


Figure: Montney Major Rock Types.

Introduction Background

The oil and gas industry is subject to production uncertainty in many ways, including:

- Finding oil and gas reserves is highly unpredictable.
- Productivity of an individual well can be forecast only approximately and even the best priors are often only weakly informative.
- Production data can be very noisy.
- Market prices for commodities move unexpectedly.
- Economic factors, such as interest rates, are unknown.

Introduction Motivation

- The industry is interested in how uncertainties are treated, especially how technical uncertainties can best be expressed during the evaluation of investment decisions.
- Basic ODEs cannot capture these uncertainties very well.
- Stochastic models offer a methodology to better capture the uncertainties of the process by treating some unknown parameters as random variables.

Introduction Goal

- To model the unknown parameters as stochastic processes.
- Solve the resulting stochastic differential equations.
- Compare the probabilistic results with data from actual wells to asses model performance.

Introduction Basic Definitions

- Flow rate (q): The mount of gas produced per time unit for several consecutive period.
- Cumulative gas production (Q): $\int_0^T q dt$
- Decline rate(D): $D = -\frac{1}{q} \frac{\Delta q}{\Delta t}$

Introduction Decline Curve Analysis

- Decline curve analysis is the systematic evaluation of trends in historic production rates from oil and gas wells, most typically how the rate of production decreases (declines) over time.
- These trends can be extrapolated forward and thus used to forecast the future performance of wells.
- Most commonly, production trends are represented using simple differential equations, for example, hyperbolic, exponential etc.

Introduction

Production Decline Curve

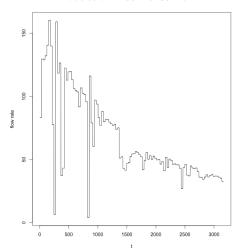


Figure: An example of the flow rate of gas from a gas well.

Data Description

X_UWI_DISPLAY	PROD_DATE [‡]	GAS [‡]
00/01-01-059-21W5/4	2011-12-01	288.3
00/01-01-059-21W5/4	2012-01-01	2080.3
00/01-01-059-21W5/4	2012-03-01	4320.6
00/01-01-059-21W5/4	2012-04-01	3744.2
00/01-01-059-21W5/4	2012-05-01	3190.2
00/01-01-059-21W5/4	2012-06-01	1478.6
00/01-01-059-21W5/4	2012-07-01	2569.7
00/01-01-059-21W5/4	2012-08-01	2301.8
00/01-01-059-21W5/4	2012-09-01	2010.4
00/01-01-059-21W5/4	2012-10-01	1626.7
00/01-01-059-21W5/4	2012-11-01	1558.5

Figure: An snapshot of the production data set.

Common PDE models in Decline Analysis

Arps:

$$\frac{dq}{dt} = -\left(\frac{D_i}{q_1^b}\right)q^{b+1}$$

Power Law Exponential:

$$\frac{dq}{dt} = -\left(D_{\infty} + D_1 t^{-(1-n)}\right) q$$

Stretched Exponential:

$$\frac{dq}{dt} = -\left(\frac{n}{t}\left(\frac{t}{\tau}\right)^n\right)q$$

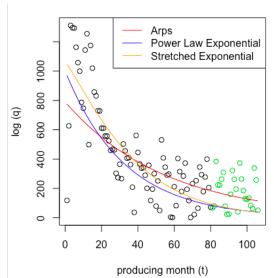
Logistic Growth:

$$\frac{dq}{dt} = -\left(\frac{a - an + (1+n)t^n}{t(a+t^n)}\right)q$$

Duong:

$$\frac{dq}{dt} = -\left(mt^{-1} - at^{-m}\right)q$$

Parameter Estimation of Classic PDE Models by LS



Improved Power Law Exponential Model NO.1

Power law exponential model:

$$log(q) = log(q_0) - D_{\infty}t - Dt^n$$
 (1)

- First, we assume $log(q_0) \sim m + \varepsilon N(0,1)$
- To generate the uncertainty in the model, we add a Brownian Motion term with a scale parameter λ : λB_t . This could correspond to the assumption that uncertainty is caused by normal errors in the measurement of production data.
- Therefore, the proposed model is:

$$log(q) = m + \varepsilon N(0,1) - D_{\infty} - Dt^{n} + \lambda B_{t}$$
 (2)

- Since the $B_t \sim N(0, \sqrt{t})$ and the well is always run for a long time, the fluctuation of model NO.1 is too large at the late time of well.
- We weight B_t with $\frac{1}{1+t}$
- Therefore, the model change to:

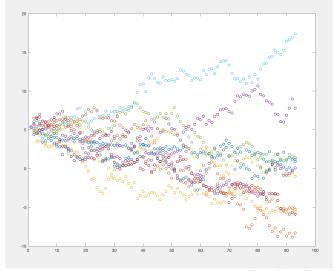
$$log(q) = m + \varepsilon N(0,1) - D_{\infty} - Dt^{n} + \frac{\lambda B_{t}}{1+t}$$
 (3)

Estimation of Model NO.2

• Then we estimate the parameters $(m, \varepsilon, D_{\infty}, D, n, \lambda)$ in the model (by Maximum Likelihood) minimizing

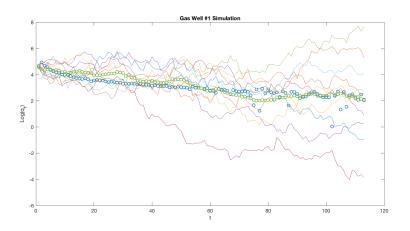
$$\begin{split} &\frac{1}{2}log(\varepsilon^{2}2\pi) + \frac{(log(q_{0}) - m_{0})^{2}}{2\pi\varepsilon^{2}} \\ &+ \sum_{i=1}^{N} \left(\frac{1}{2}log\left(\frac{\lambda^{2}2\pi}{(1+t_{i-1})^{2}}\right) + \frac{(log(q_{t_{i}}) - log(q_{t_{i-1}}) + D_{\infty} + Dt_{i}^{n})^{2}}{2\pi\lambda^{2}} \right) \end{split}$$

Estimation Result



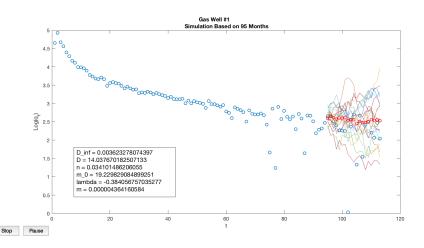
- We improve the model
- Then the log-likelihood: find $(m_0, \varepsilon, \lambda, m, D, D_{\infty})$ minimizing

$$\begin{split} &\frac{1}{2}log(\varepsilon^2 2\pi) + \frac{(log(q_0) - m_0)^2}{2\pi\varepsilon^2} \\ + &\sum_{i=1}^{N} \left(\frac{1}{2}log(\frac{\lambda^2 2\pi}{(1 + t_{i-1}^m)^2}) + \frac{(log(q_{t_i}) - log(q_{t_{i-1}}) + D_{\infty} + Dt_{i-1}^n)^2}{2\pi\lambda^2} \right) \end{split}$$



- Improve the model
- Modify the log-likelihood: find $(m_0, \varepsilon = 0, \lambda, m, D, D_{\infty})$ minimizing

$$\begin{split} & \sum_{i=1}^{N} log(\frac{2\pi\lambda^{2}}{(1+t_{i}^{m})^{2}}) \\ & + \sum_{i=1}^{N} (log(q_{t_{i}} - log(q_{t_{i-1}}) + D_{\infty} + Dnt_{i}^{n-1})^{2} \frac{(1+t_{i-1}^{m})^{2}}{2\pi\lambda^{2}} \\ & + \kappa \sum_{i=1}^{N} |m_{0} - D_{\infty}t_{i} - Dt_{i}^{n} - log(q_{i}^{obs})| \end{split}$$



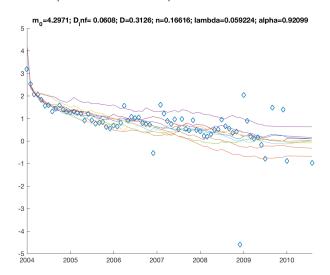
Improved Power Law Exponential Model NO.4

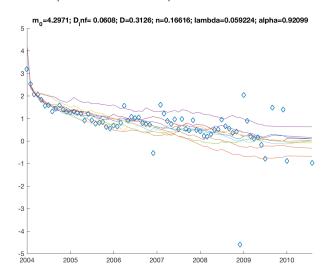
- Instead of Brownian Motion we could consider the case that a Poisson process describes the physical processes underlying the uncertainty. This could correspond to an assumption of random changes in pumping rate or back-pressure occurring at random time intervals.
- Simply, we replace the Brownian Motion by a Poisson Process N_t^{α} :

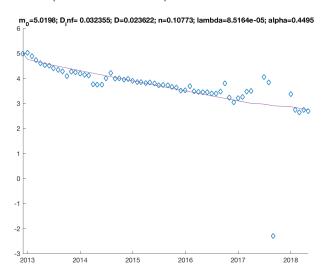
$$log(q) = m + \varepsilon N(0,1) - D_{\infty} - Dt^{n} + \lambda N_{t}^{\alpha}$$
 (4)

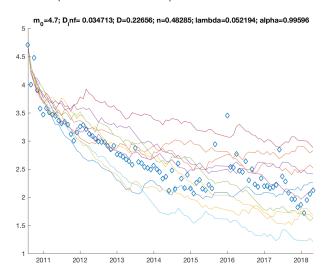
• Then the least square norm: $(\varepsilon = 0)$: find $(m_0, \lambda, m, D, D_{\infty}, \alpha)$ minimizing

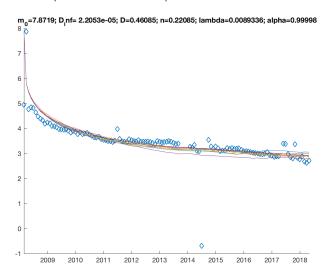
$$\begin{aligned} &E\sum_{i=1}^{N}\left(\Delta log(q_{t_{i}}^{mod})-\Delta log(q_{t_{i}}^{obs})\right)^{2} \\ &+\kappa\sum_{i=0}^{N}\left(Elog(q_{t_{i}}^{mod})-log(q_{t_{i}}^{obs})\right)^{2} \end{aligned}$$

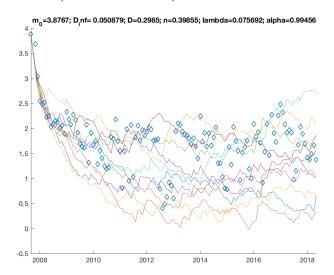


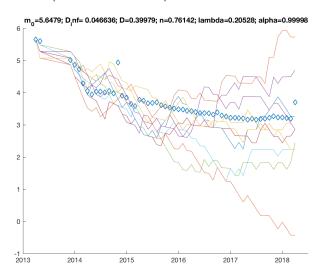


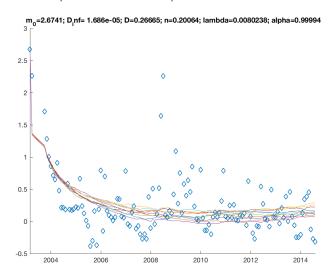












Summary Future Work

- It may be possible to improve the fit of uncertainty in the model for instance by combining Poisson and Brownian Motions.
- Find the spatial correlation between the gas production of wells in a region of interest, and use the correlation to forecast the performance of a new site based on the old wells around it.
- Relate the gas production forecast to the energy market forecast to calculate the profit in the future.

Thank You!