

Big Data in Oil and Gas: An Application of Time Series Analysis to Improve Probabilistic Forecasting of Production from Marcellus Wells

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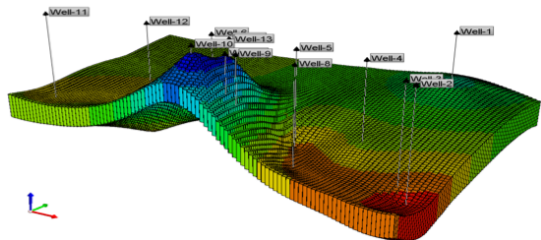
PETROLEUM AND NATURAL GAS ENGINEERING

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Estimating Reservoir Production

Methods to predict production (flow rate) from a well penetrating a reservoir:

- Volumetric Calculation
- Material Balance
- Reservoir Simulation
- Decline Curves



Decline Curves

- Initially developed for conventional reservoirs
- Challenge to find one that works well for shale gas reservoirs (and unconventionals in general)
 - Heterogeneous porosity and permeability
 - Micro-permeability in shale matrix has different physics governing fluid flow

Probabilistic Production Forecasting

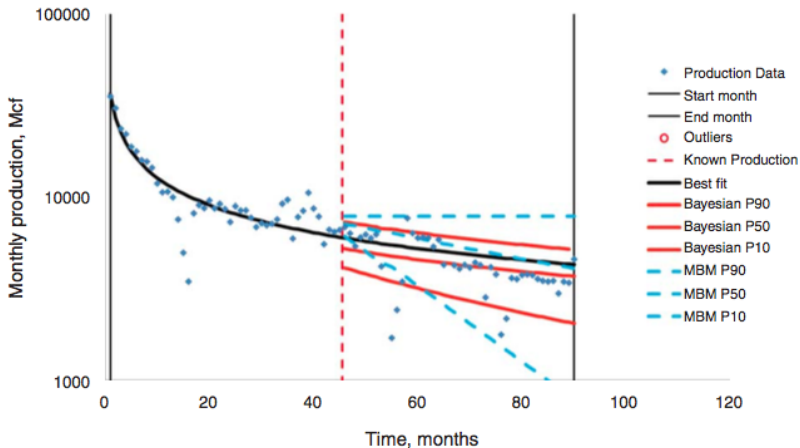
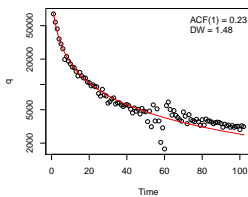


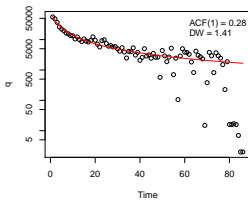
Figure is from Gong et al. (2014), which proposes Bayesian approach. Modified Bootstrap Method was proposed by Cheng et al. (2010).

Autocorrelation in Decline Curve (Hyperbolic) Residuals

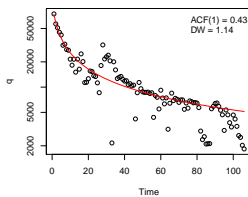
well1



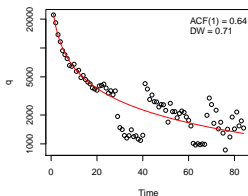
well2



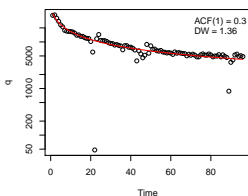
well4



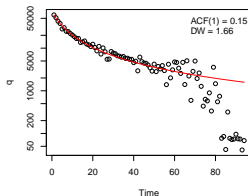
well6



well8

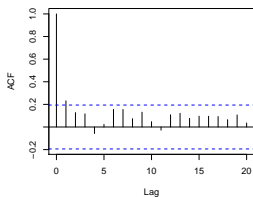


well9

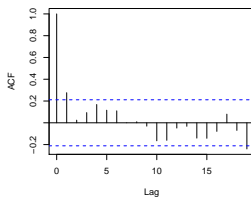


Autocorrelation in Decline Curve (Hyperbolic) Residuals

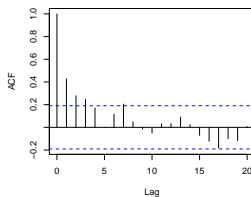
well1



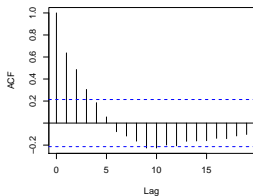
well2



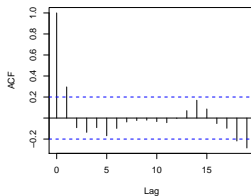
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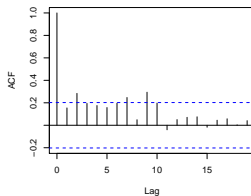
well6



well8



well9



Bayesian Hierarchical Model: Decline Curve

Let $q(t; \theta)$ be a generic term for any decline curve modeling flow rate q over time t . The shape of the curve is defined by a set of parameters θ . Therefore, the observed flow rates q_t are:

$$\ln(q_t) = \ln(q(t; \theta)) + \epsilon_t \quad (1)$$

$$\theta \sim \pi(\beta) \quad (2)$$

$$\epsilon_t \sim N(0, \sigma_\epsilon = 1/\sqrt{\tau}) \quad (3)$$

$$\tau \sim \text{Gamma}(0.001, 0.001) \quad (4)$$

$\pi(\beta)$ is generically describing the set of prior distributions for the decline curve parameters.

Bayesian Hierarchical Model: Decline Curve with AR1

To add in a first-order autoregressive term:

$$q_t = q(t; \theta) + v_t \quad (5)$$

$$v_t = \phi v_{t-1} + \epsilon_t \quad (6)$$

$$\theta \sim \pi(\beta) \quad (7)$$

$$\epsilon_t \sim N(0, \sigma_\epsilon = 1/\sqrt{\tau}) \quad (8)$$

$$\tau \sim \text{Gamma}(0.001, 0.001) \quad (9)$$

$$\phi \sim N(0, 1) \quad (10)$$

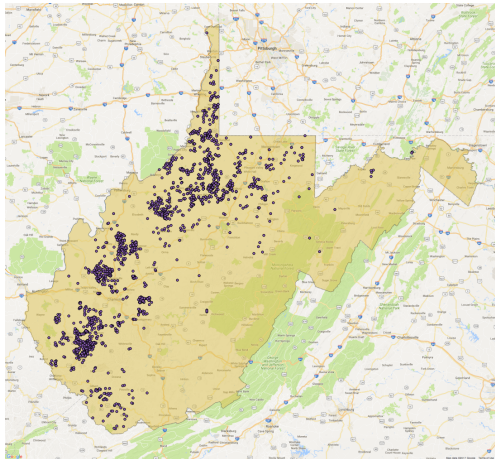
Decline Curve Parameter Prior Distributions

Defining $\theta \sim \pi(\beta)$:

Decline Curve Name	Functional Form	Prior Distributions for Parameters
Exponential	$q_t = q_i \exp(-D_i t)$	$q_i \sim \text{lognormal}(q_1, \log_{10}(\exp(q_1)))$ $D_i \sim \text{lognormal}(\ln(-(q_2 - q_1)), 1)$
Hyperbolic/Harmonic	$q_t = q_i(1 + D_i b t)^{-1/b}$	q_i, D_i as above $b \sim \text{lognormal}(0, 2)$
Power Law Loss-ratio	$q_t = q_i \exp(-D_\infty t - D_i t^n)$	q_i, D_i as above $D_\infty \sim \text{lognormal}(\ln(1e^{-5}), 0.2)$ $n \sim \text{uniform}(0, 1)$
Stretched Exponential	$q_t = q_i \exp(-(t/\tau)^n)$	q_i, n as above $\tau \sim \text{lognormal}(2, 1)$
Logistic Growth	$q_t = K n t^{n-1} / (a + t^n)^2$	$K \sim \text{lognormal}(14, 3)$ $n \sim \text{lognormal}(\ln(0.9), 10)$ $a \sim \text{lognormal}(4, 2)$

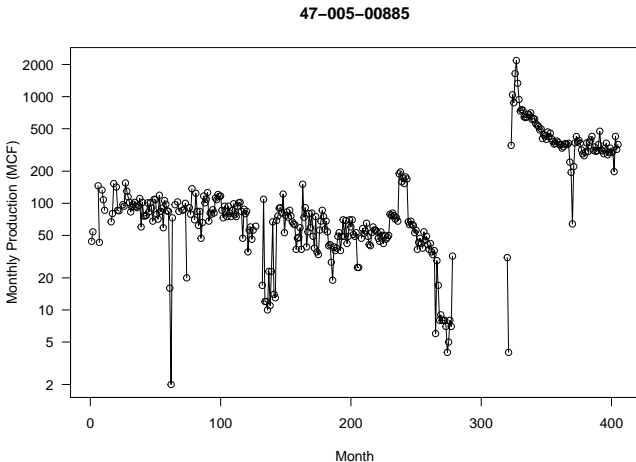
Bayesian regression is performed via Gibbs sampling (JAGS), with 8 chains running for 50,000 iterations. The first 25,000 samples are discarded (“burn-in”), and every 100th sample thereafter is retained (“thinning”), leaving 2,000 samples from the posterior distributions.

West Virginia Marcellus Wells



- 2,467 wells in all

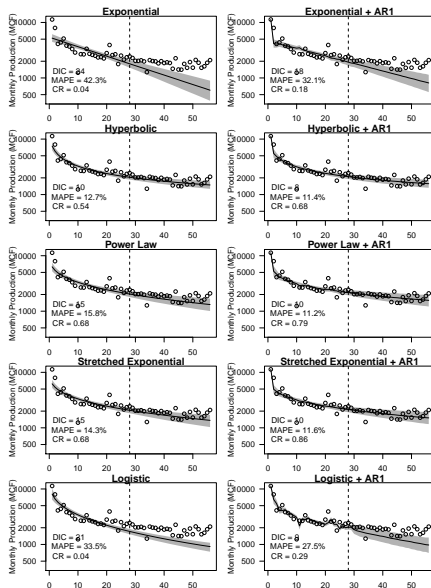
Sample Filtering and Pre-processing



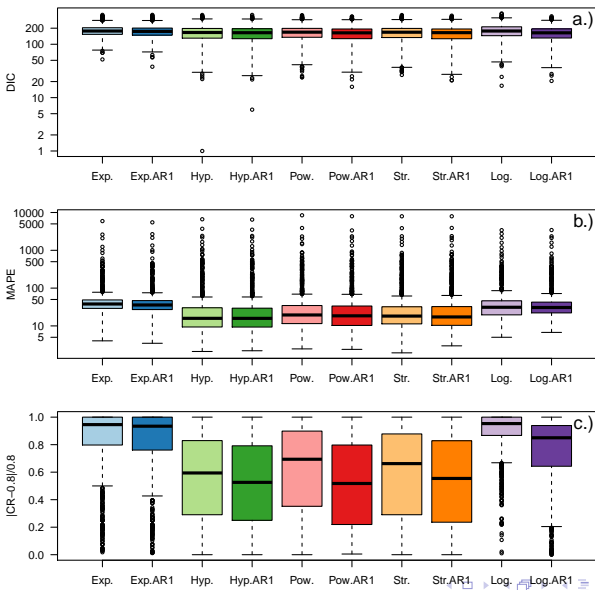
Of the 2,467 total wells, 1,007 wells with continuous records of at least 3 years in duration were selected for analysis.

MCMC

Example: API 47-033-05143, Harrison County, WV



Summary of all 1,007 wells



Hypothesis Testing

One-sided paired t-tests:

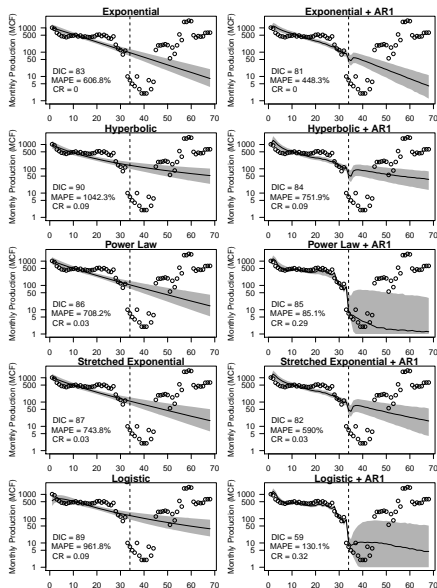
- Means of differences:

	Exp	Hyp	Pow	Str	Log
DIC w/ AR1 < DIC w/o AR1	-4.81	-3.02	-7.47	-6.20	-17.68
MAPE w/ AR1 < MAPE w/o AR1	-2.45	-1.99	-2.90	0.22	-1.76
$ CR - 0.8 /0.8$ w/ AR1 < $ CR - 0.8 /0.8$ w/o AR1	-0.01	-0.04	-0.11	-0.06	-0.14

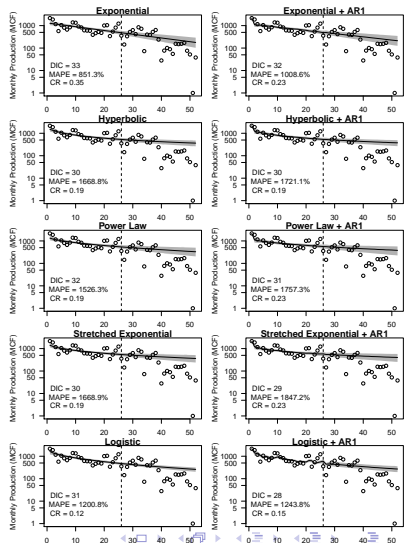
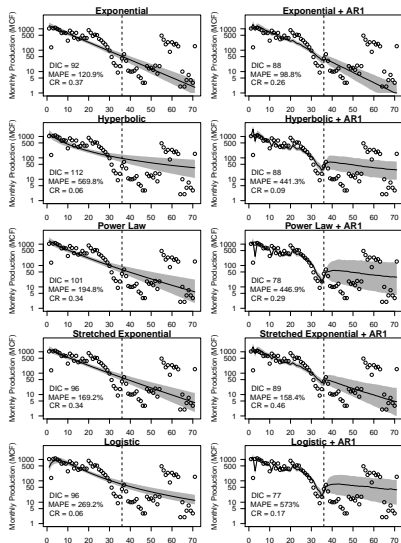
- p-values:

	Exp	Hyp	Pow	Str	Log
DIC w/ AR1 < DIC w/o AR1	3.6e-60	2.9e-21	1.1e-64	1.1e-61	6.4e-114
MAPE w/ AR1 < MAPE w/o AR1	1.9e-05	4.8e-05	0.0063	0.73	0.051
$ CR - 0.8 /0.8$ w/ AR1 < $ CR - 0.8 /0.8$ w/o AR1	0.00031	3.1e-20	3.4e-47	1.7e-28	2.6e-97

Best case w.r.t. MAPE: API 47-087-04638



Worst cases w.r.t. MAPE: API 47-035-02852 & 47-035-02961



Conclusion

References

- Cheng, Y., Wang, Y., McVay, D., Lee, W. J., Apr. 2010. Practical Application of a Probabilistic Approach to Estimate Reserves Using Production Decline Data. SPE Economics & Management 2 (01), 19–31.
- Gong, X., Gonzalez, R., McVay, D. A., Hart, J. D., Dec. 2014. Bayesian Probabilistic Decline-Curve Analysis Reliably Quantifies Uncertainty in Shale-Well-Production Forecasts. Spe Journal 19 (06), 1,047–1,057.