Underground Reservoir Identification Using Generalized Wellbore Data

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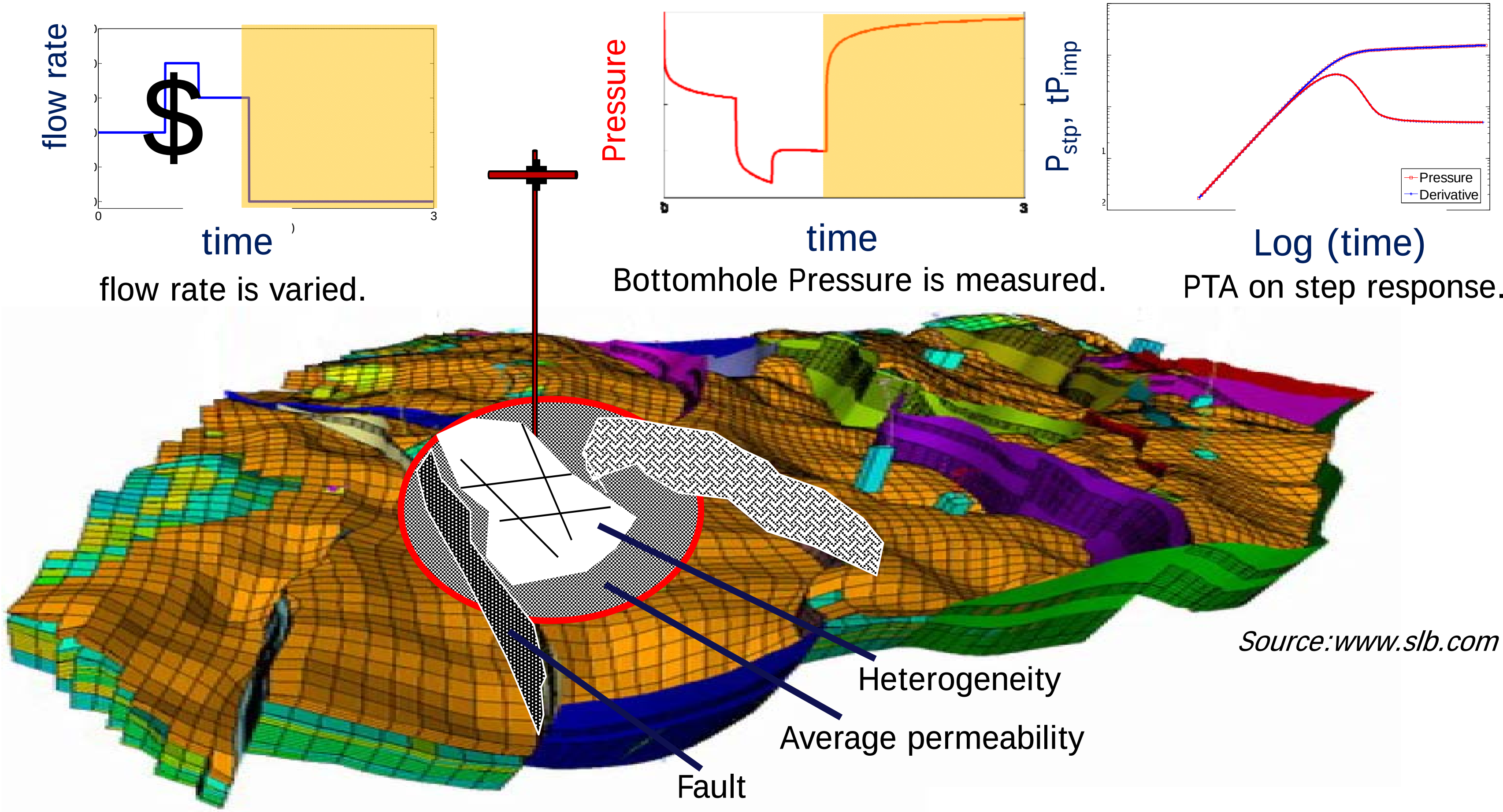
4: University of Calgary

Well Testing



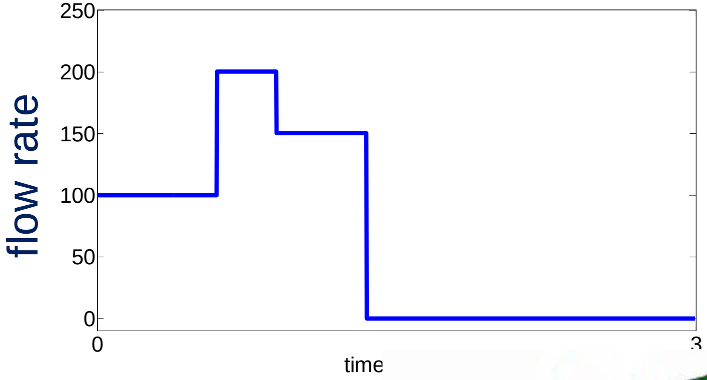
- ❑ **Permeability** distribution determines flow pattern of hydrocarbon in the reservoir.
- ❑ Most representative permeability information data around the wells by **well test.**

Problem Statement

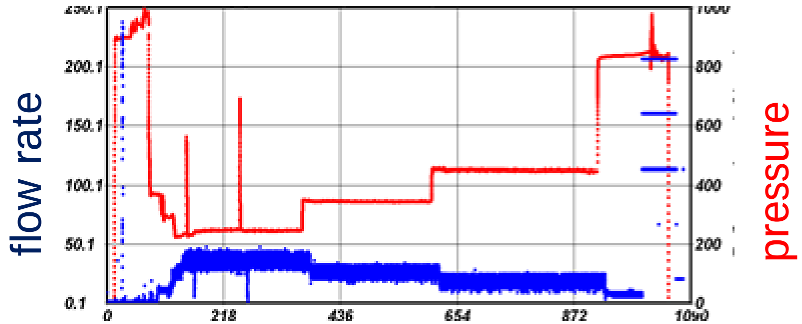
Our goal is to do well test analysis on variable flow rate data and obtain reservoir information

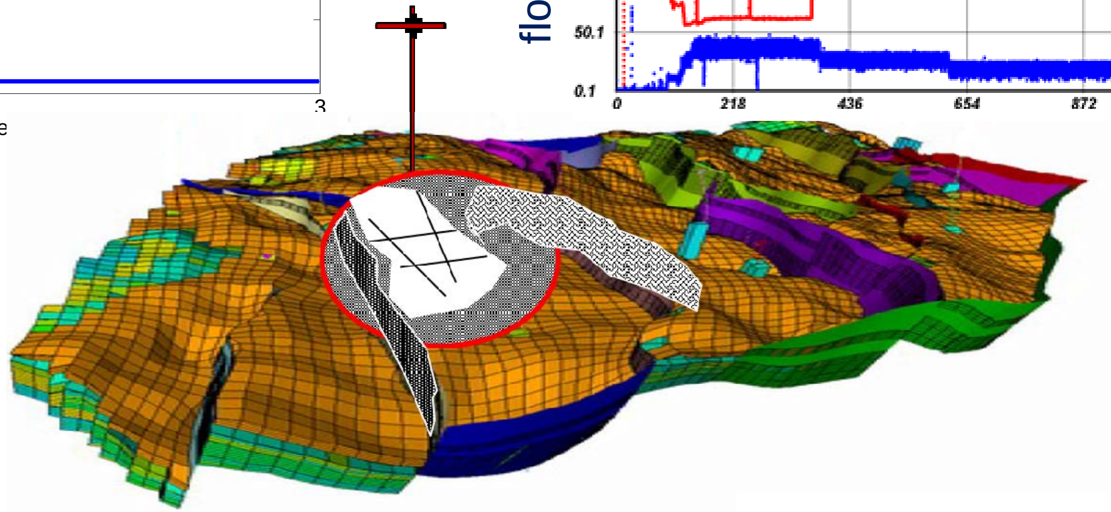
Sources of variable rate data

Variable rate well test



Permanent downhole data





Outline

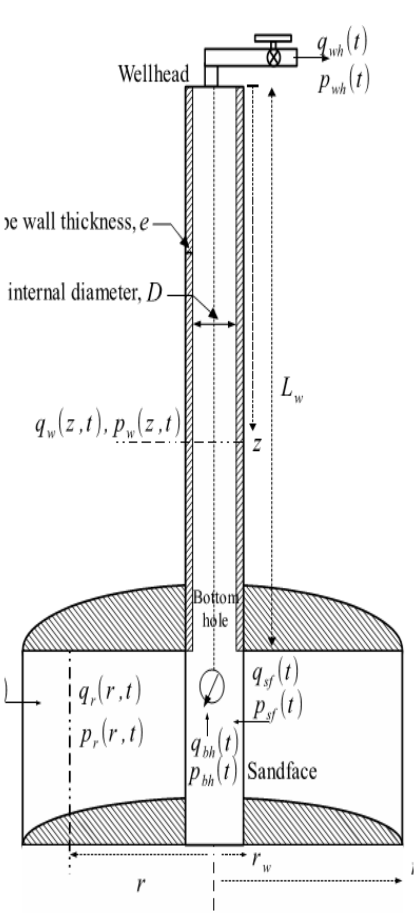
- ❑ Well test analysis in the system identification framework
- ❑ EIV problem with IV
- ❑ Physical parameter estimation
- ❑ Experimental results

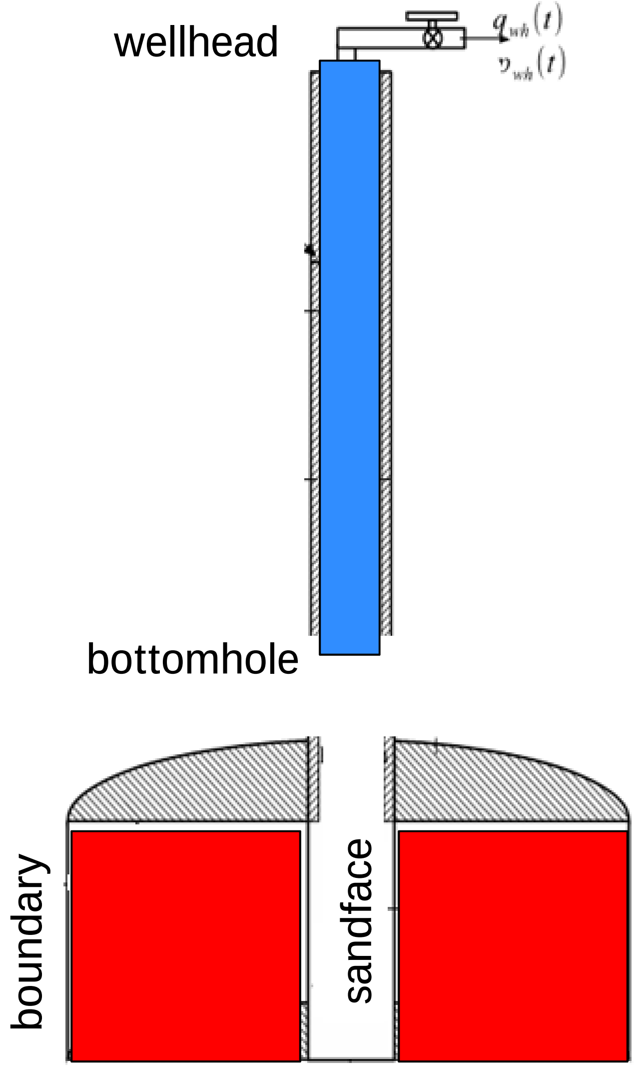
Problem in well test :

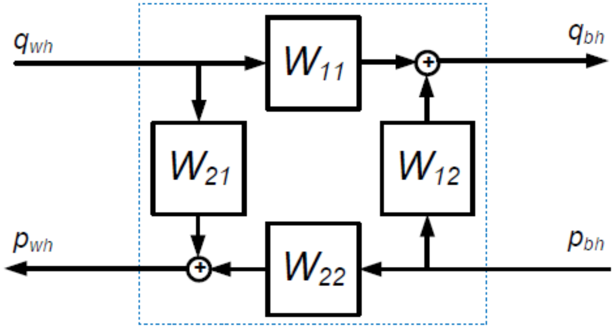
Given a set of measured (noisy) $p^m{}_{bh}$, and variable (noisy) $q^m{}_{bh}$

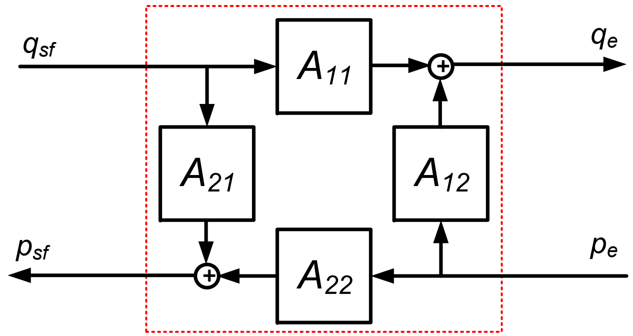
Identify the reservoir model (and corresponding physical properties)

Port-based Modelling of Production System

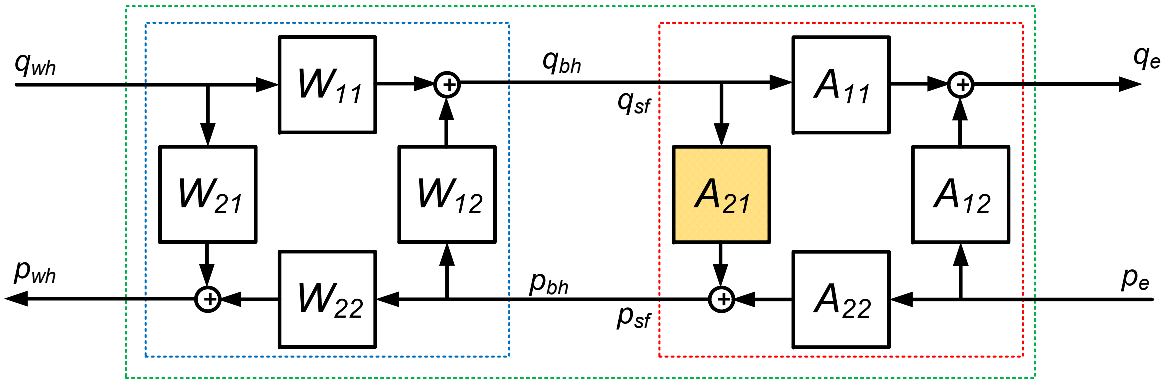


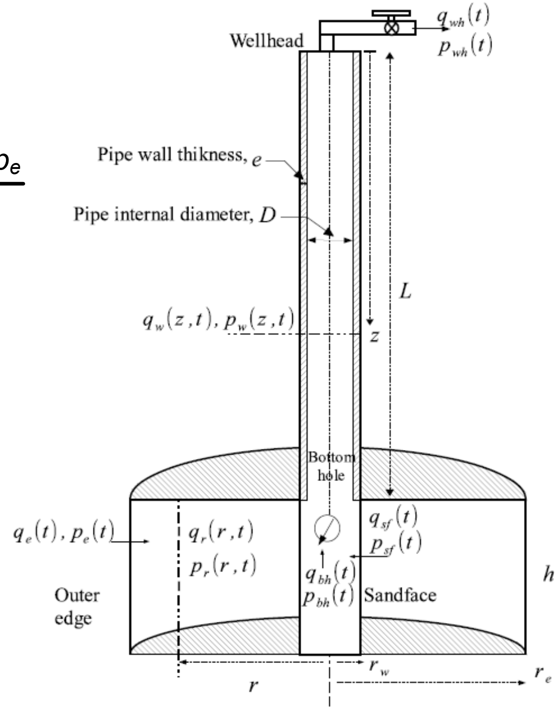




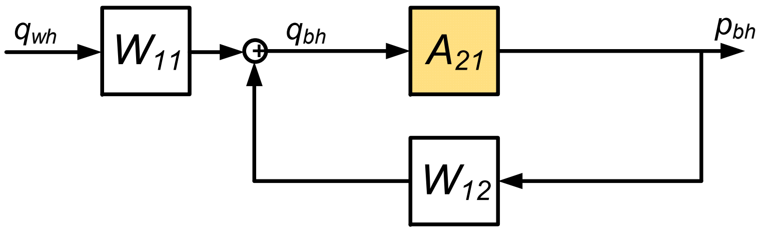


Bilaterally Coupling the Systems

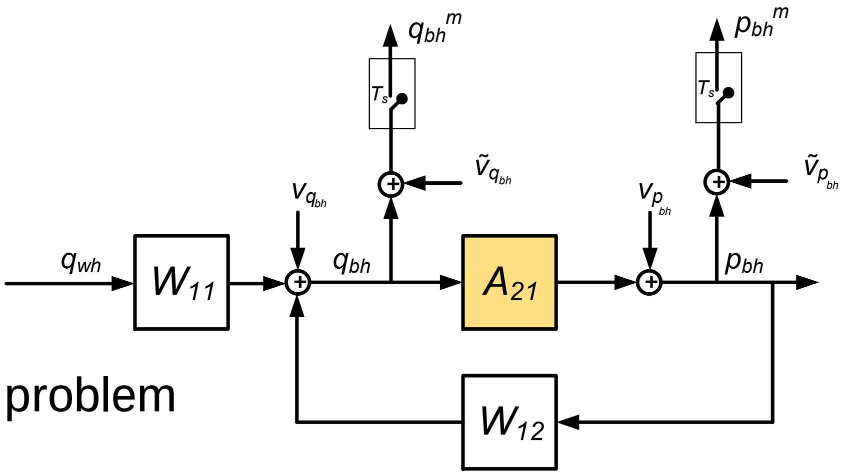




After simplification and keeping the relevant terms:



Well Test Measurements



A Errors-In-Variable (EIV) in Closed Loop problem

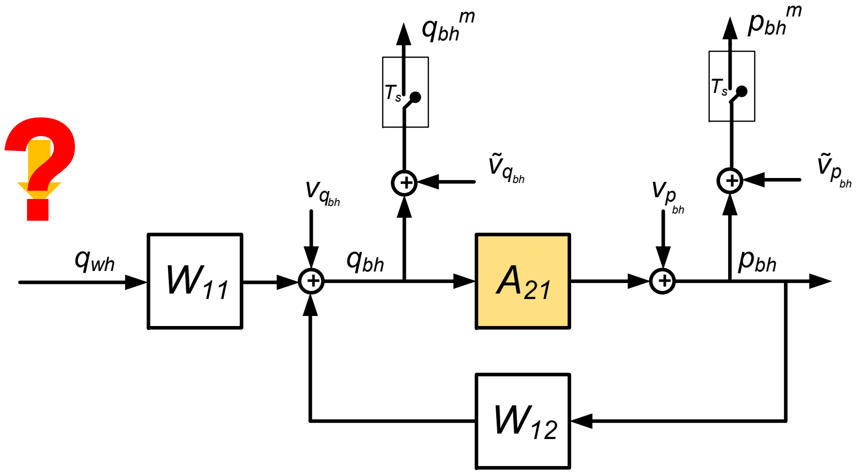
$$q_{bh}^{m}(k) = (W_{11}S)(q^{-1})q_{wh}(k) + w_q(k),$$

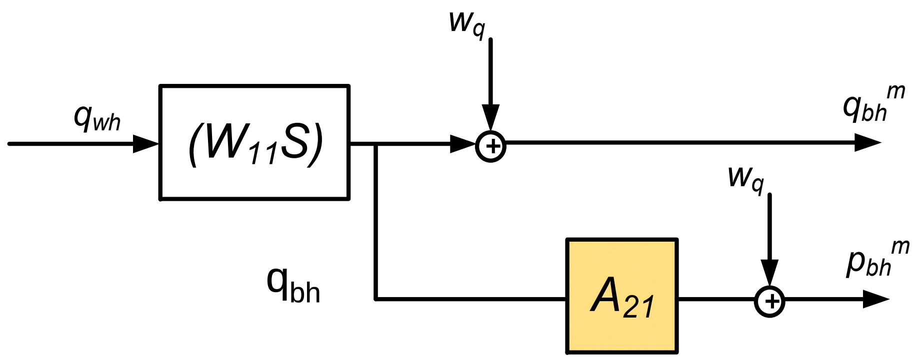
$$p_{bh}^{m}(k) = (A_{21}W_{11}S)(q^{-1})q_{wh}(k) + w_p(k).$$

Identifiability analysis shows that in general A_{21} can not be identified uniquely on the basis of the noisy input and output signals only

(Söderström, 2013)

Two-stage Closed-loop Identification

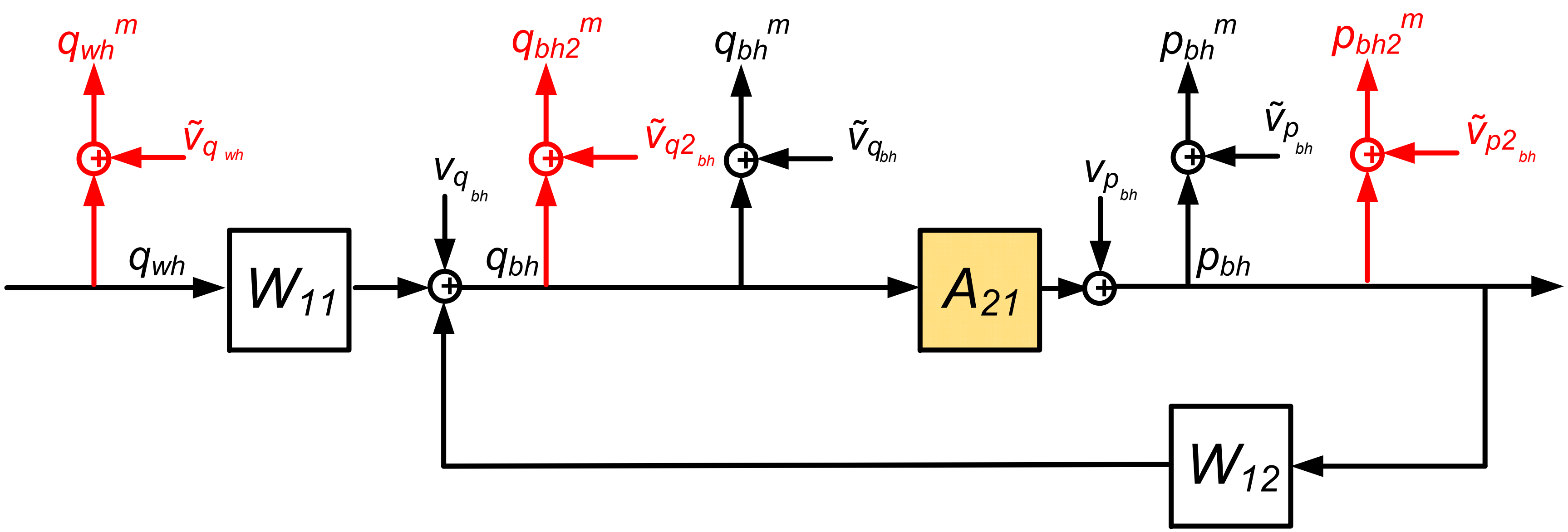




can be interpreted as iv-method, with iv-signal q_{wh}

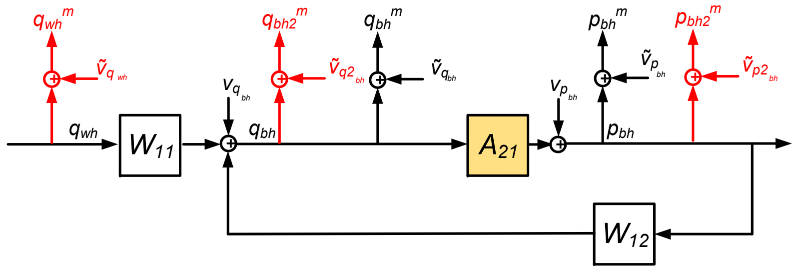
Alternative Options

Using other measurements in the system as
Instrumental Variable (IV) signal



EIVIV algorithm

Dankers et al., IFAC 2014; Automatica, Jan 2016



Plant data generating system

$$p_{bh}^{m}(k) = A_{21}(q^{-1})q_{bh}(k) + w_p(k)$$

One-step predictor signal

$$\varepsilon(\tau,\theta) = H^{-1}(q^{-1},\theta)\left[p_{bh}^{m}(\tau) - G(q,\theta)q_{bh}(\tau)\right]$$

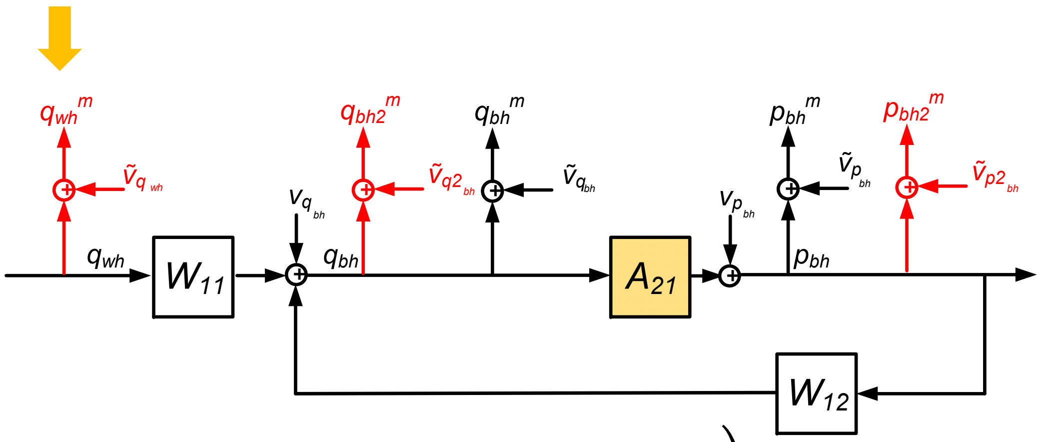
Using IV signal, denoted as z, and calculate the cross-correlation with the predictor signal:

$$R_{\varepsilon z}(\tau,\theta) = H^{-1}(q,\theta)\left(R_{p_{bh}^{m}z}(\tau) - G(q,\theta)R_{q_{bh}z}(\tau)\right)$$

$$= H^{-1}(q,\theta)\left(A_{21}(q^{-1})R_{q_{bh}z}(\tau) + R_{w_p z}(\tau) - G(q,\theta)R_{q_{bh}z}(\tau)\right)$$

$$= H^{-1}(q,\theta)\left(A_{21}(q^{-1})R_{q_{bh}^{m}z}(\tau) + R_{w_p z}(\tau) - G(q,\theta)R_{q_{bh}^{m}z}(\tau)\right)$$

EIVIV algorithm



$$R_{\varepsilon z}(\tau,\theta) = H^{-1}(q,\theta)\left(A_{21}(q)R_{q_{bh}^m z}(\tau) + R_{w_p z}(\tau) - G(q,\theta)R_{q_{bh}^m z}(\tau)\right)$$

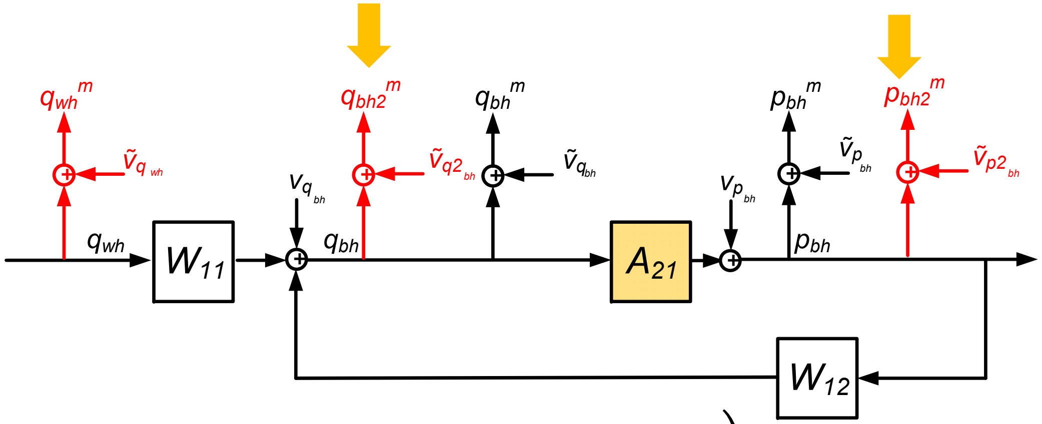
Case 1: z is uncorrelated with w_p then $R_{w_p z}(\tau)$=0.

Thus $A_{21}(q^{-1}) = G(q,\theta)$ iff $R_{\varepsilon z}(\tau,\theta) = 0$ for all τ

Hence by having $V_N(\theta^*) = \frac{1}{N}\sum_{\tau=0}^{N-1} R_{\varepsilon z}^2(\tau,\theta^*) = 0$ then $R_{\varepsilon z}(\tau,\theta^*) = 0$

and consequently $A_{21}(q^{-1}) = G(q,\theta^*)$.

EIVIV algorithm



$$R_{\varepsilon z}(\tau,\theta) = H^{-1}(q,\theta)\left(A_{21}(q)R_{q_{bh}^m z}(\tau) + R_{w_p z}(\tau) - G(q,\theta)R_{q_{bh}^m z}(\tau)\right)$$

Case 1: z is correlated with w_p then

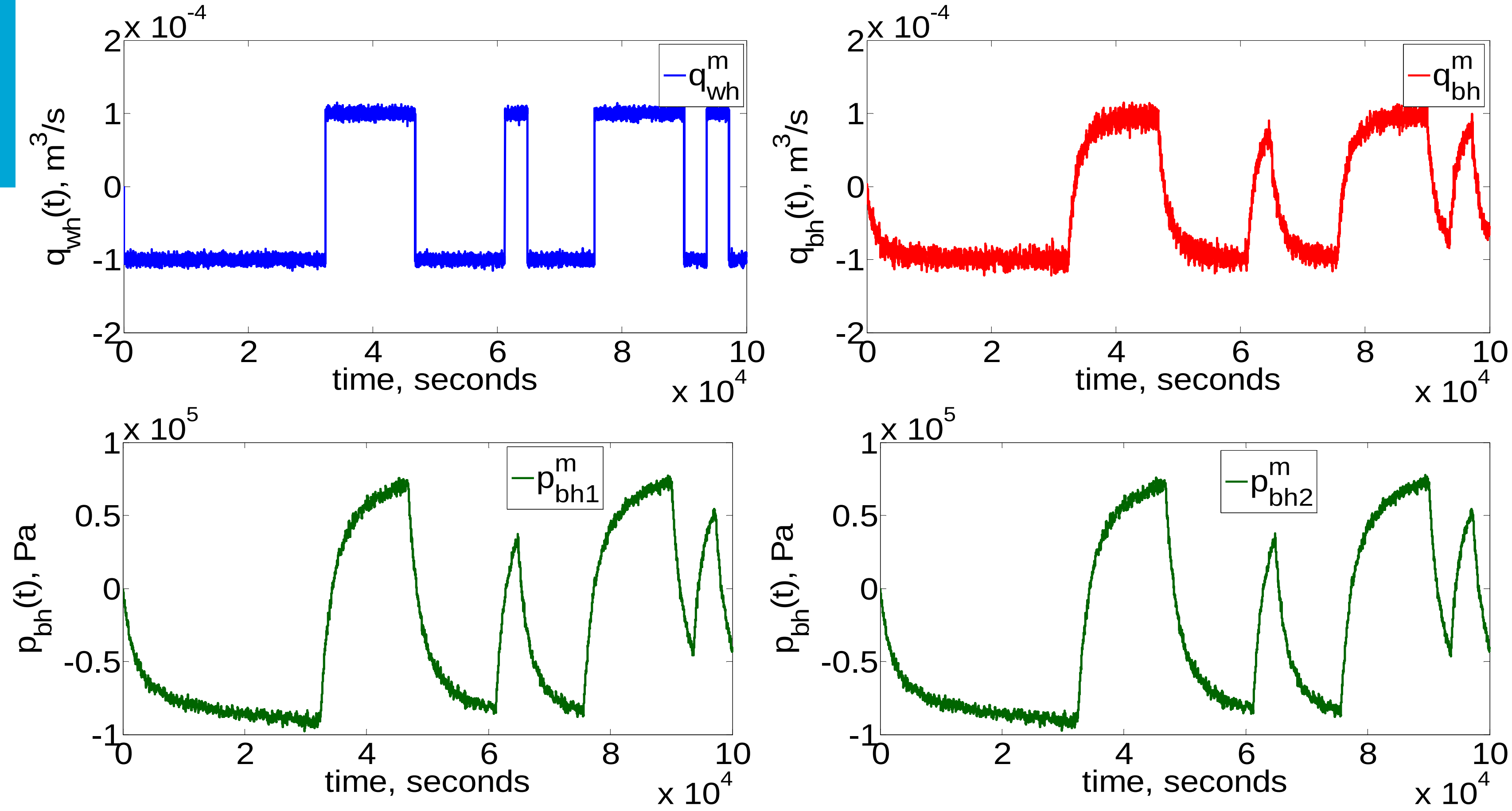
$$R_{\varepsilon z}(\tau,\theta) = H^{-1}(q,\theta)\left(A_{21}(q)R_{q_{bh}^m z} - G(q,\theta)R_{q_{bh}^m z}\right) + \bar{E}[H^{-1}(q,\theta)H^0(q)e(t)z(t-\tau)]$$

Thus $\{A_{21}(q^{-1}) = G(q,\theta)\ \&\ H(q,\theta) = H^0(q)\}$ iff $R_{\varepsilon z}(\tau,\theta) = 0,\ \tau \geq 0$

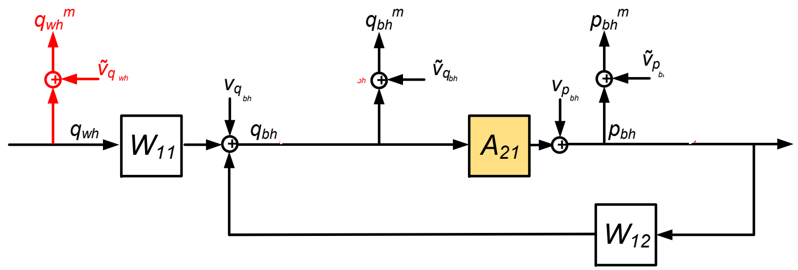
Hence by having $V_N(\theta^*) = \frac{1}{N}\sum_{\tau=0}^{N-1} R_{\varepsilon z}^2(\tau,\theta^*) = 0$ then $R_{\varepsilon z}(\tau,\theta^*) = 0$

and consequently $A_{21}(q^{-1}) = G(q,\theta^*)$.

Case Studies:

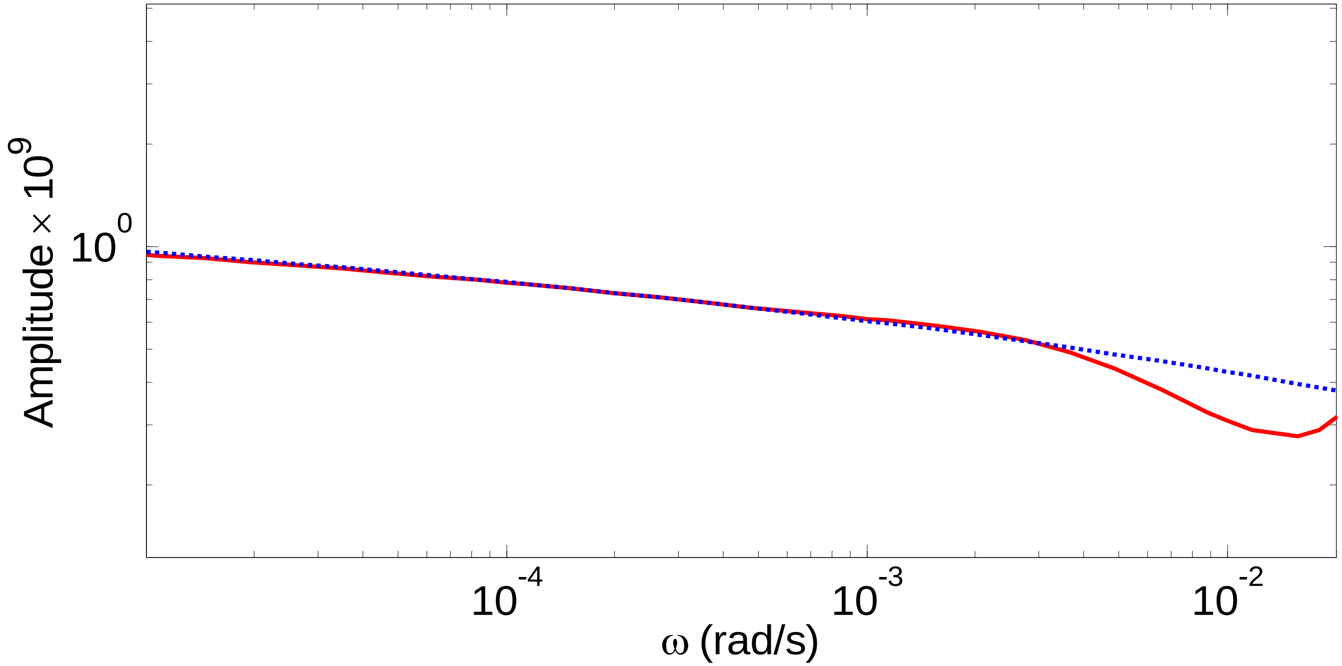


Case 1: Using q_{wh}^{m}



Instrumental variable $z = q_{wh}^{m}$

Identified model = OE(660)

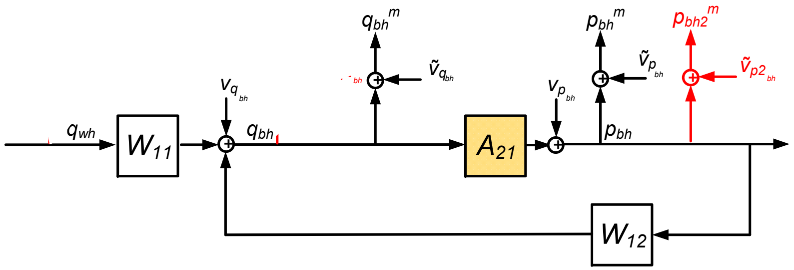


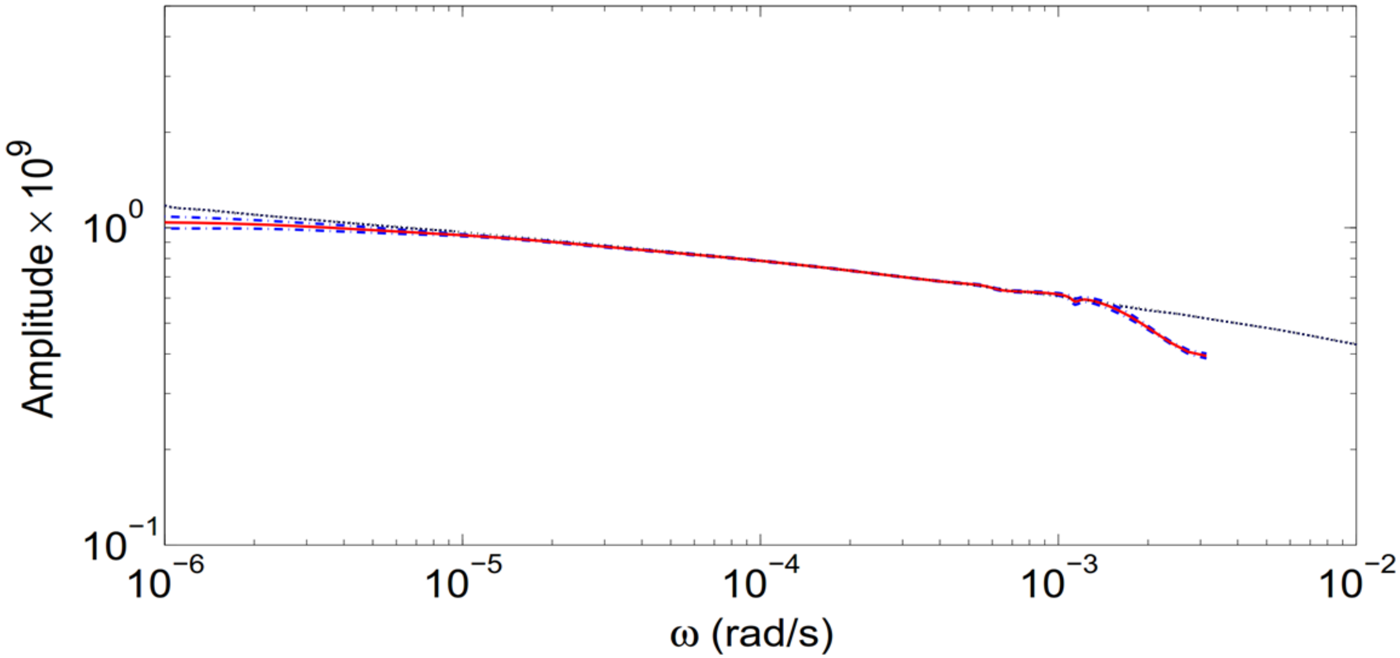
Amplitude plot of the identified plant model,
red: identified model, dotted-blue: data generating system (k=200 mD, S=0)

Case 2: Using p_{bh}^m

Instrumental variable $z = p_{bh}^m$

Identified model = BJ(9 9 9 10 0)





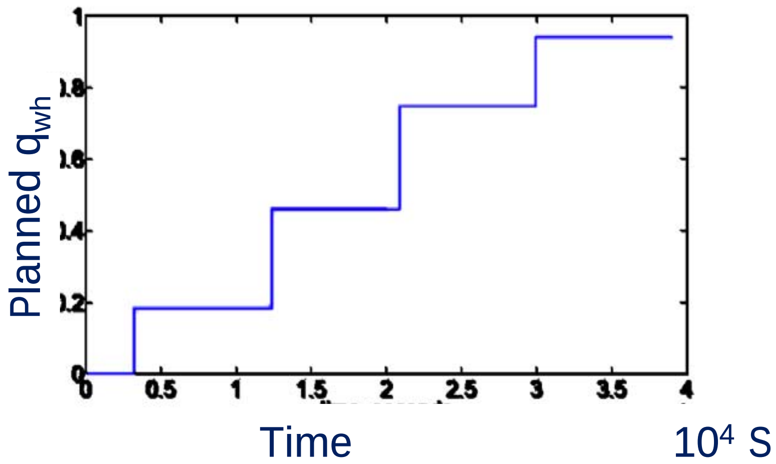
Amplitude plot of the identified plant model

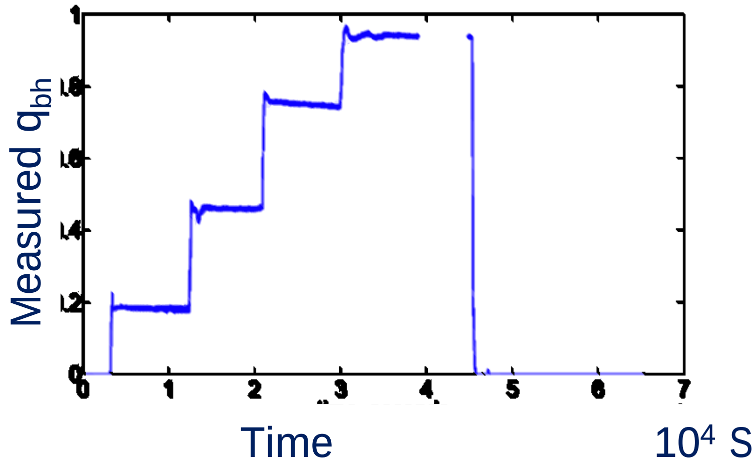
red: identified model, dotted-blue: data generating system (k=200 mD, S=0)

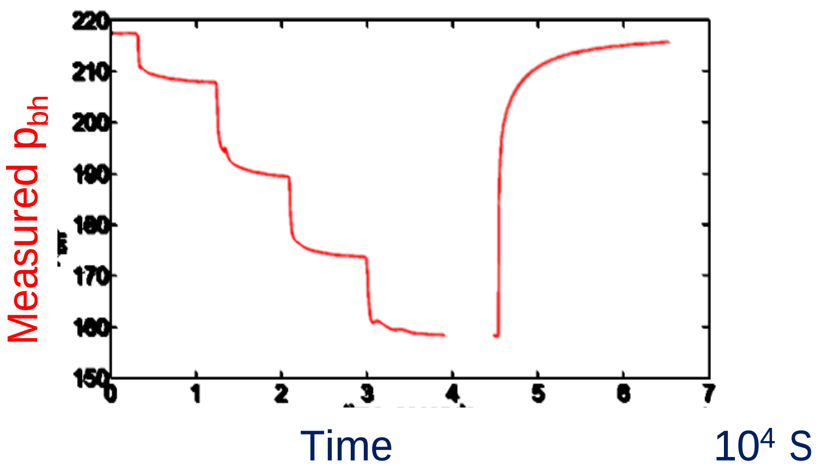
Physical Parameters Estimation

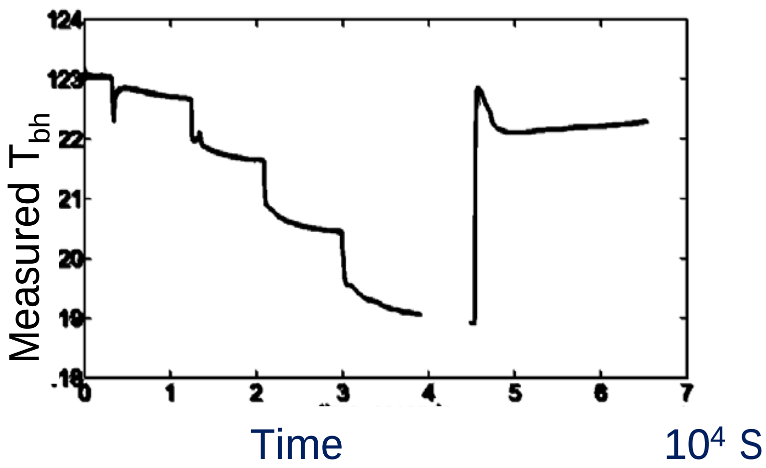
	Physic-based model	Data-based model
Time-domain	PDE equations	discrete-time data
Complex-domain	$A_{21}(s) = A_{21}(s, k, S)$	$\hat{G}_{ss}(z, \hat{\theta}_N) = \dfrac{B(z, \hat{\theta}_N)}{F(z, \hat{\theta}_N)}$
Frequency-domain	$A_{21}(j\omega, k, S\ )$	$\hat{G}_{ss}(e^{j\omega}, \hat{\theta}_N)$
Misfit criterion	$\beta = \frac{1}{L} \underset{\beta}{\operatorname{argmin}} \sum_{l=1}^{L} \left\| A_{21}(\beta, j\omega_l) - \hat{G}_{ss}(e^{j\omega}, \hat{\theta}_N) \right\|^2 W(\omega_l)$	
Results	Permeability k & Skin factor S	

Results: Field Data





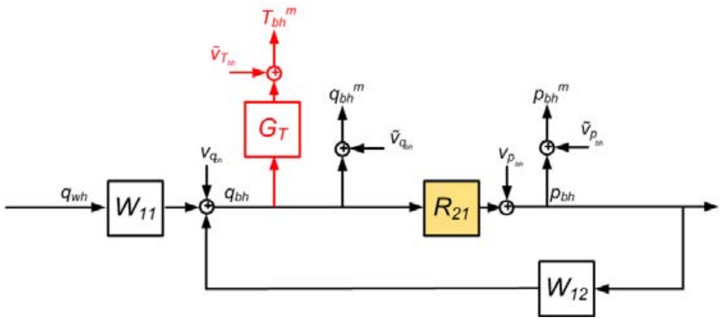


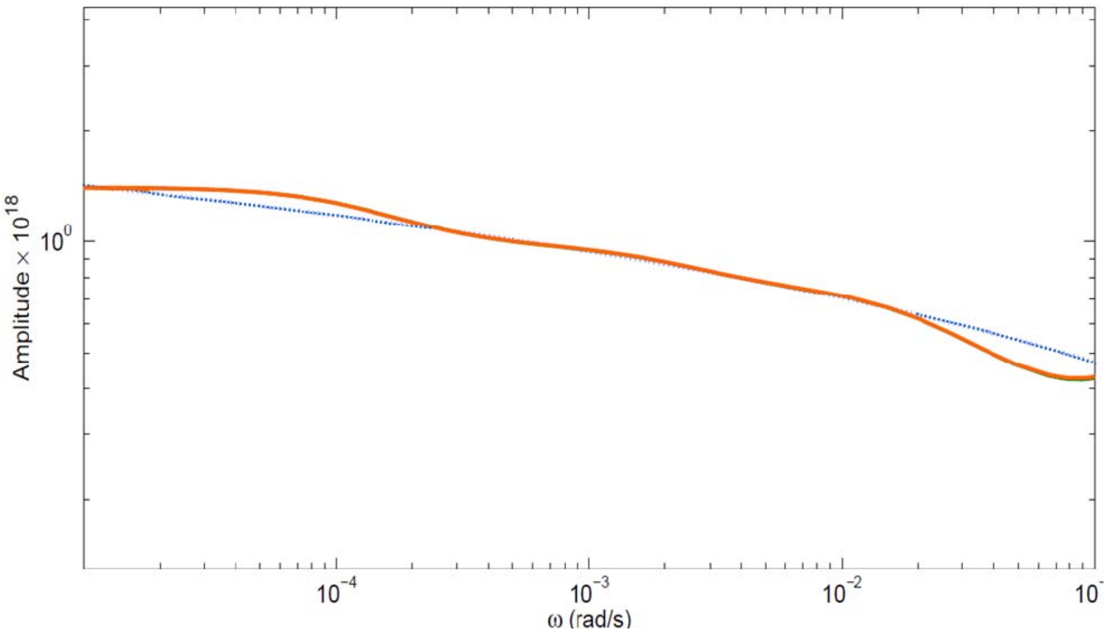


Identified Model

Instrumental variable $z = T_{bh}^{m}$

Identified model = BJ(6 6 7 8 0)



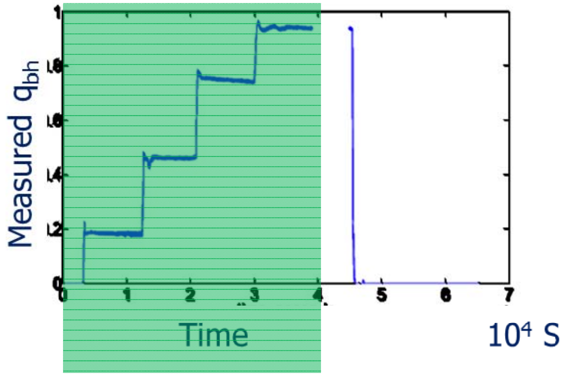


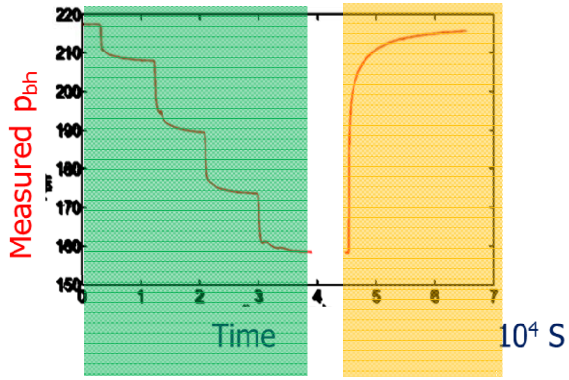
Amplitude plot of the identified plant model

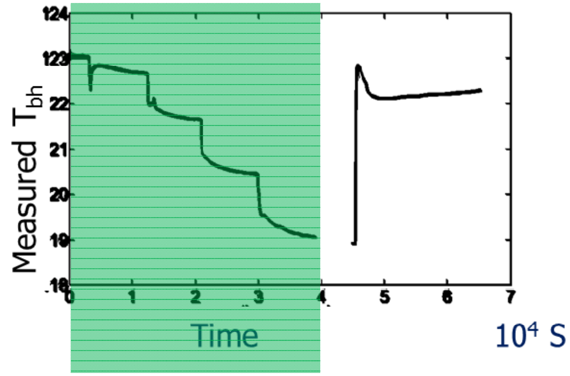
orange: identified model,

dotted-blue: estimated physics-based model (k=15.8 mD, S=-1.4)

Physical Parameter Estimates







Identified model using EIVIV		Conventional Well test analysis	
k	S	k	S
15.8 mD	-1.4	11 mD	-2.6

Results are in good correspondence with each other.

Discussion and Conclusions

- Well model identification can be described as a closed-loop EIV identification problem.
- This allows well testing on the basis of general data (no need for shut-in)
- Different auxiliary measured signals can be used for solving the identifiability issue in well testing using the very powerful method of EIVIV.

THANKS FOR YOUR ATTENTION.