Electromechanical Dynamic State and Parameter Estimation Using PMU Data

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State and parameter estimation

State and parameter estimation

- Steady State estimation

  Known: Parameters, measurements: P, Q, |V|
  Estimation: |V|, θ

AE vs. DE

- Dynamic State estimation (observer, Kalman filter)

  Known: Parameters, measurements
  Estimation: dynamic states

- Dynamic State/parameter estimation

  Known: measurements
  Estimation: dynamic states and parameters

Machine parameter and state estimation using digital fault recorder (DFT)

- States and parameters related to **eletromagnetic** transient (resistance and inductances of armature winding, field resistance, magnetizing inductance)
- Sampling rate (many samples per cycle)

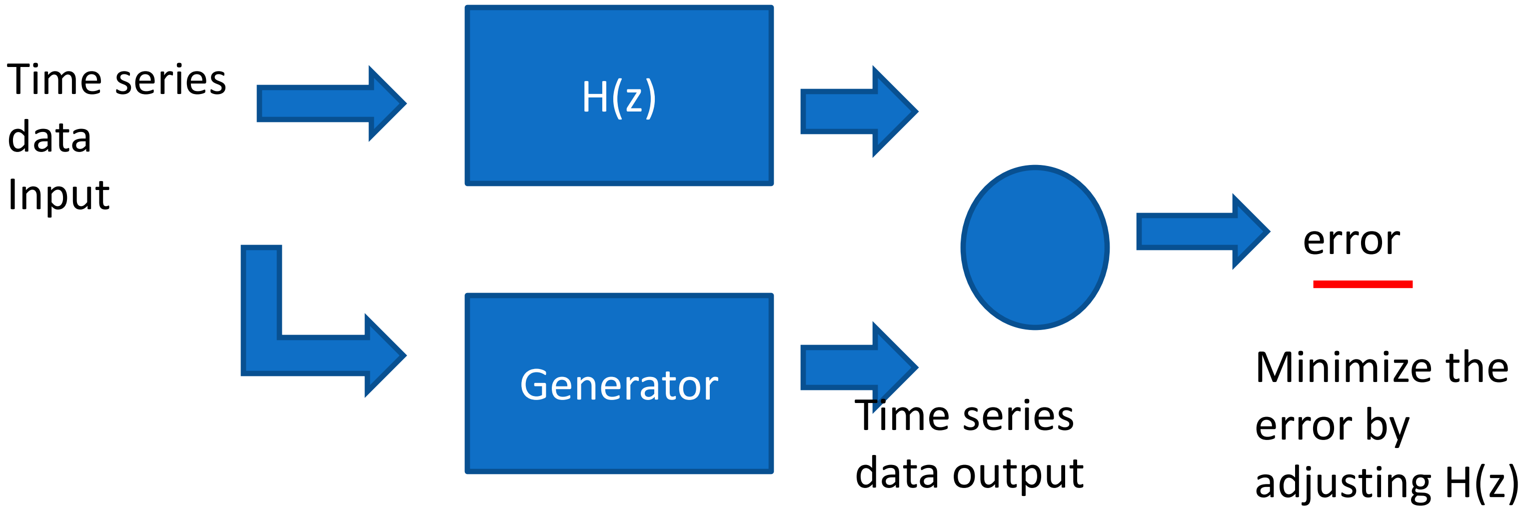
- J. Melgoza, G. Heydt, A. Keyhani, B. Agrawal, and D. Selin, “Synchronous machine parameter estimation using the hartley series,” IEEE Trans. Energy Convers., vol. 16, no. 1, pp. 49–54, mar 2001.
- E. Kyriakides, G. Heydt, and V. Vittal, “Online parameter estimation of round rotor synchronous generators including magnetic saturation,” IEEE Trans. Energy Convers., vol. 20, no. 3, pp. 529–537, sep 2005.
- J. Melgoza, G. Heydt, A. Keyhani, B. Agrawal, and D. Selin, “An algebraic approach for identifying operating point dependent parameters of synchronous machines using orthogonal series expansions,” IEEE Trans. Energy Convers., vol. 16, no. 1, pp. 92–98, mar 2001.
- E. Kyriakides, G. Heydt, and V. Vittal, “On-line estimation of synchronous generator parameters using a damper current observer and a graphic user interface,” IEEE Trans. Energy Convers., vol. 19, no. 3, pp. 499–507, sep 2004.

PMU data

- 30 Hz or 60 Hz
- Voltage/current magnitude and synchronized phase angles
- Can capture dynamics in phase angles and frequencies
- Make estimation of states and parameters related with electro-mechanical dynamics possible

Two general methods in state or parameter estimation

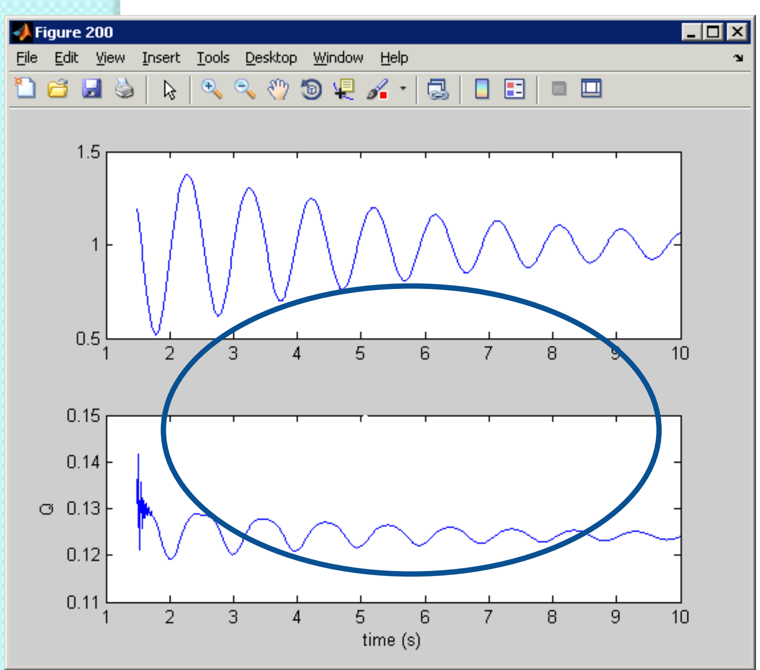
- Given a time window of data (input and output), determine parameters of the transfer function to have least squared error between estimation and measurement. –Matlab System Identification Toolbox

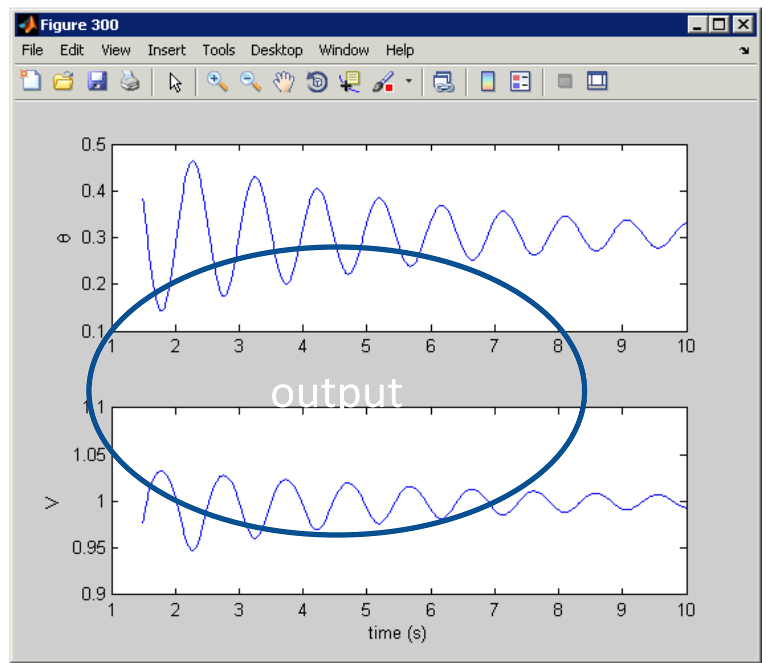


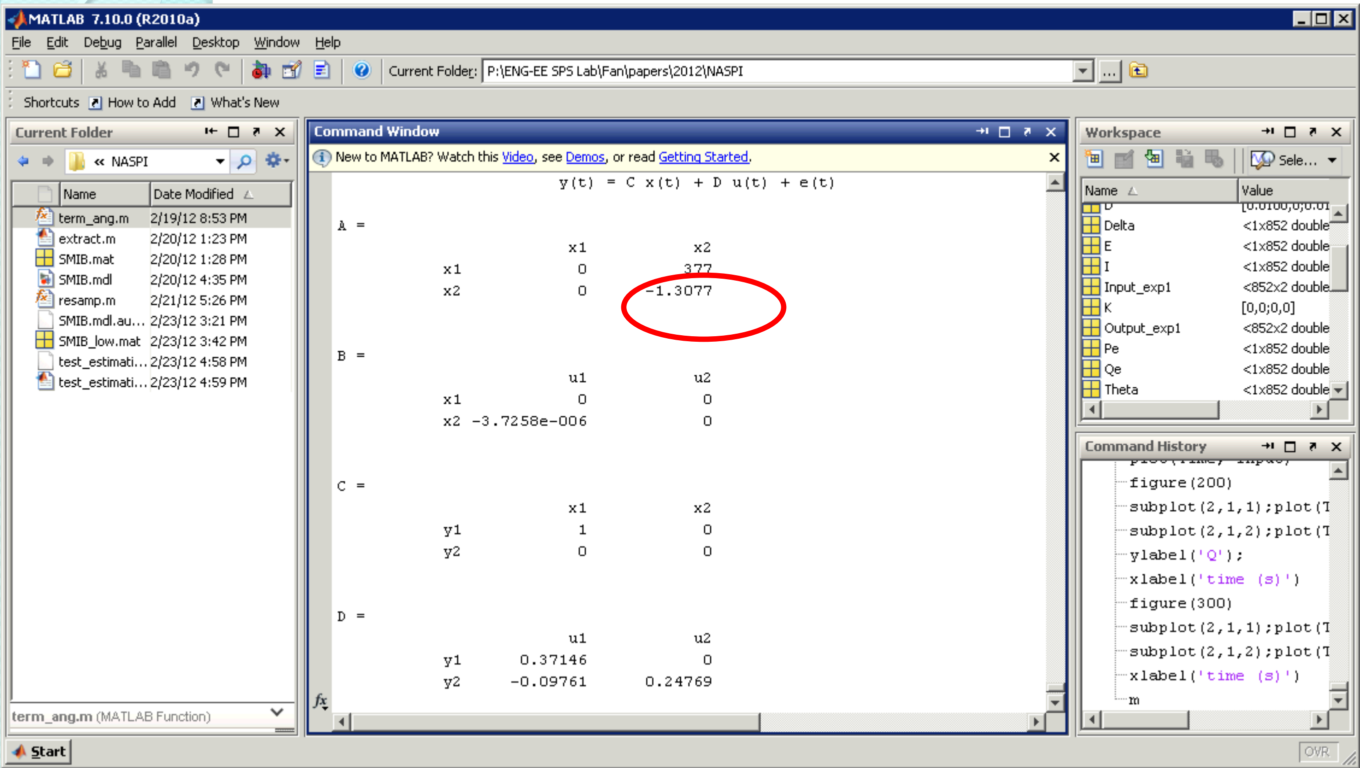
Structured state-space model estimation

$$\begin{bmatrix} \Delta\dot{\delta} \\ \Delta\dot{\omega} \end{bmatrix} = \begin{bmatrix} 0 & \omega_0 \\ 0 & -\dfrac{D}{2H} \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta\omega \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ -\dfrac{1}{2H} & 0 \end{bmatrix} \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix}$$

$$\begin{bmatrix} \Delta\theta \\ \Delta V \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta\omega \end{bmatrix} + \begin{bmatrix} C_1 & C_2 \\ C_3 & C_4 \end{bmatrix} \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix}$$



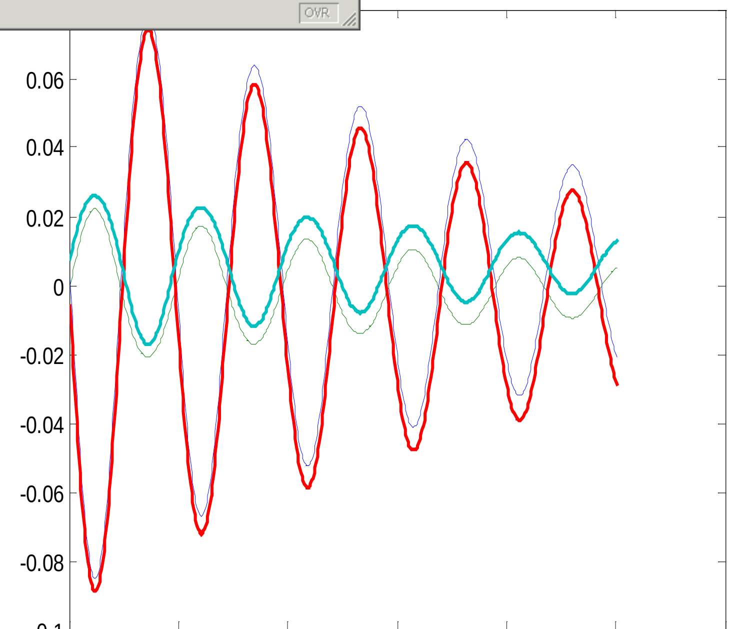




Estimated parameters are not close to the true values.

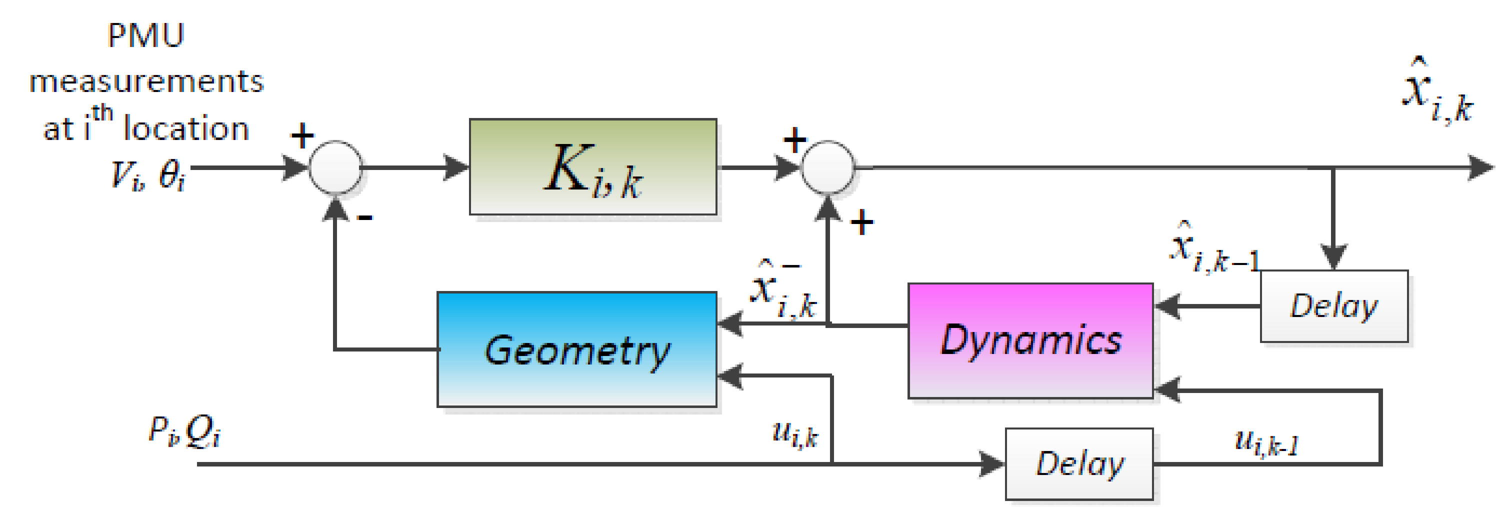
Reasons: need careful derivation of the model – current model: too many parameters to be estimated.

Measurements and simulated results from the estimation model:



The other general method

- Kalman filter -Classical Kalman filter is the optimal minimum mean square estimator when the observations are continuously available



The current step estimation is determined by the previous step estimation and current step measurement only. Estimates are given at "real-time" or every simulation step.

Previous applications: machine circuit parameters (Heydt), voltage magnitude and frequency (A. Gigis)

PMU data: PNNL

Feature: model sensitivity

How does it work?

$$\hat{x}_{k+1} = A_k \hat{x}_k + B_k u_k + w_k$$

$$\hat{y}_{k+1} = C_{k+1} \hat{x}_{k+1} + D_{k+1} u_{k+1} + v_k$$

Kalman Gain

1. prediction based on last estimate:

$$\hat{x}^-_{k+1} = A_k \hat{x}_k + B_k u_k$$

$$\hat{y}_{k+1} = C_{k+1} \hat{x}^-_{k+1} + D_{k+1} u_{k+1}$$

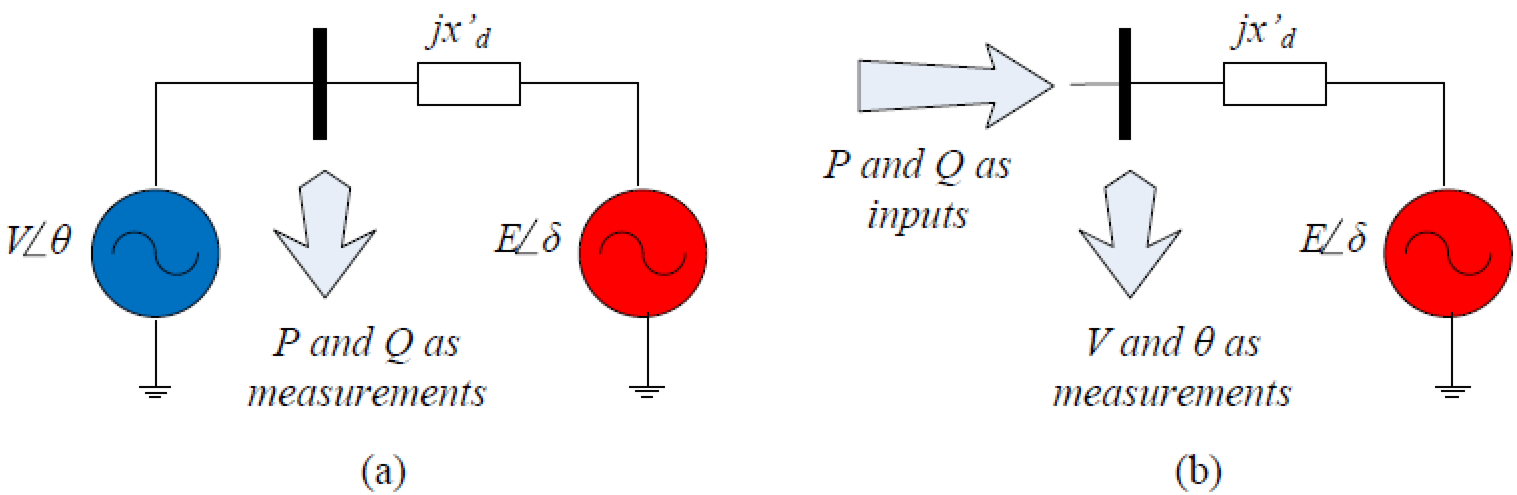
2. calculate correction based on prediction and current measurement:

$$G_k (y_{k+1} - C\hat{x}^-_{k+1} - Du_{k+1})$$

3. update prediction:

$$\hat{x}_{k+1} = \hat{x}^-_k + G_k (y_{k+1} - C\hat{x}^-_{k+1} - Du_{k+1})$$

Model decoupling

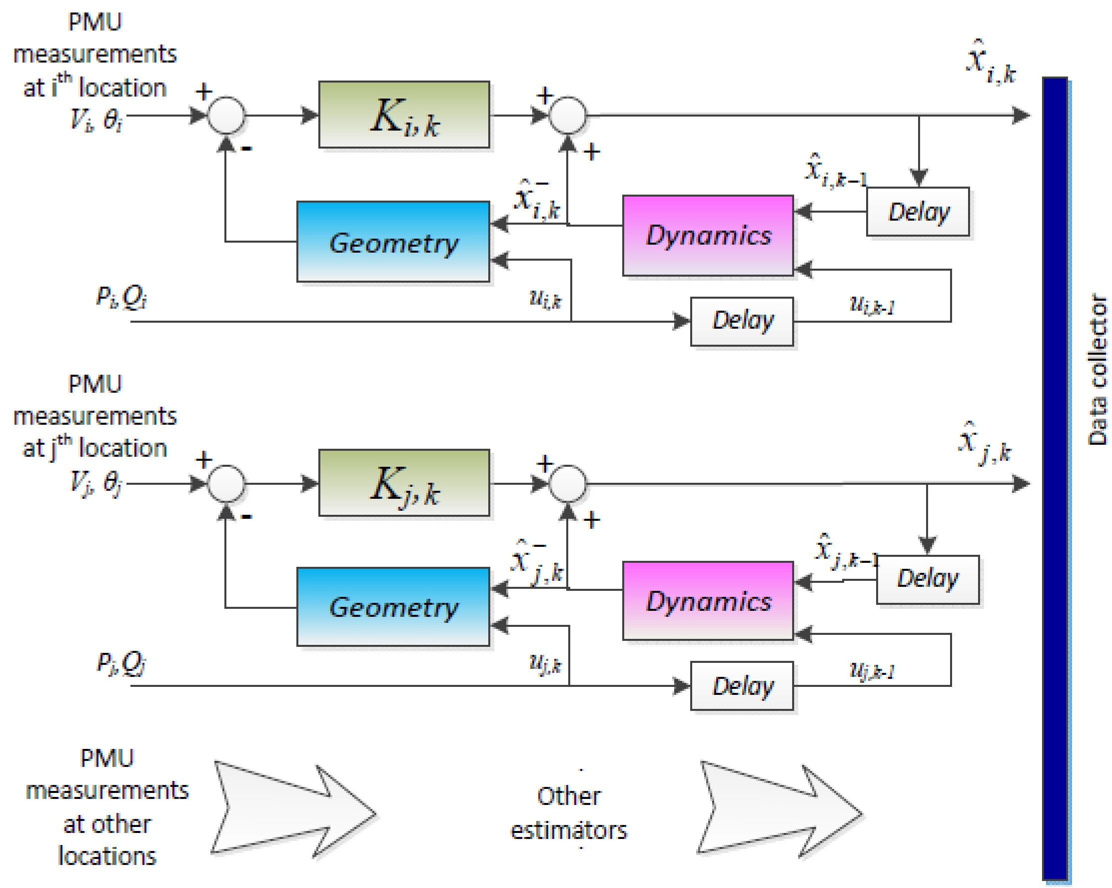


Reduce estimation model
Estimate a subsystem a time

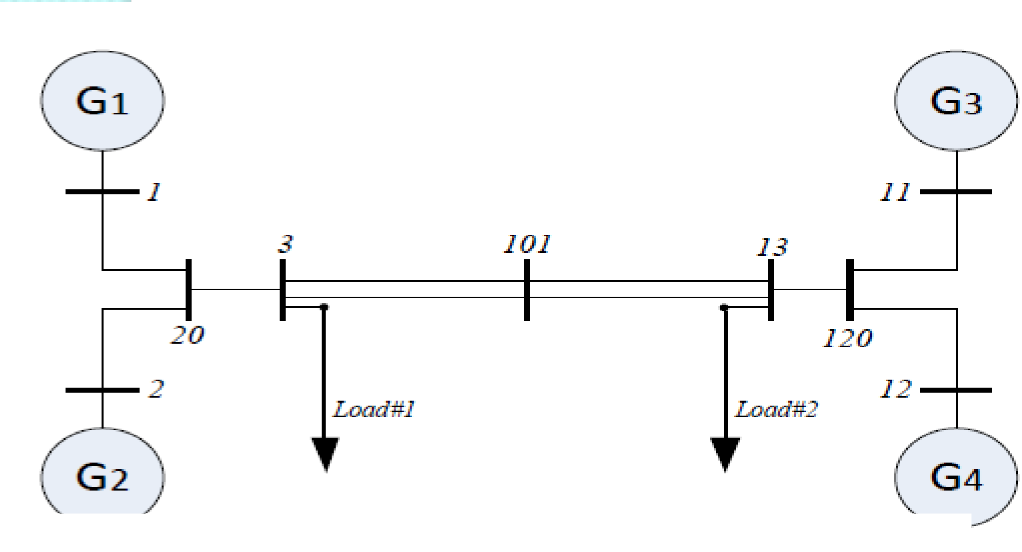
Measurement: (V, θ, P_e, Q_e)

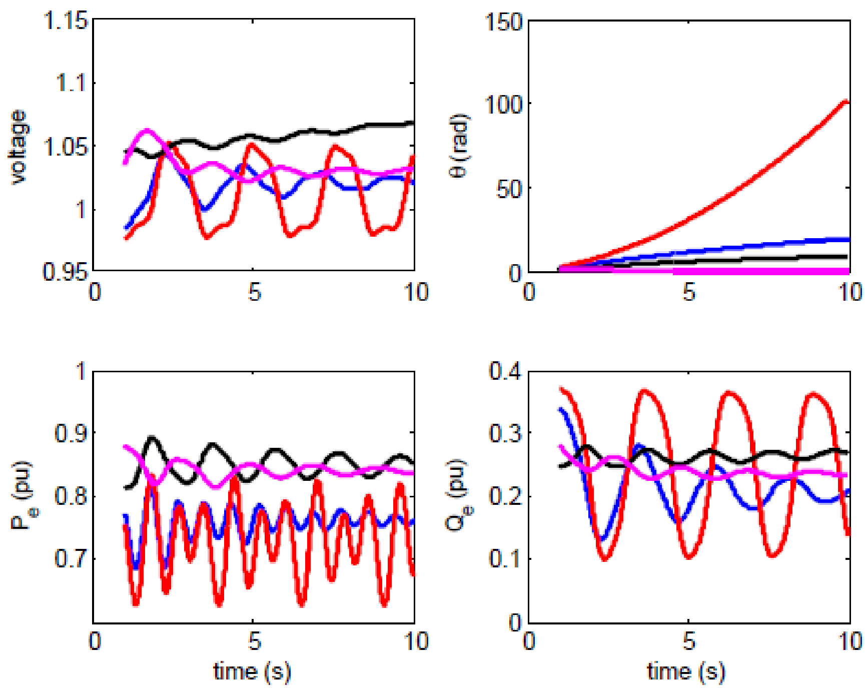
Estimation 1: 2 states (angle, speed) 4 parameters (H, D, Pm, xd')
Estimation 2: 2 states (angle, speed) 5 parameters (H, D, Pm, xd' and E)

Parallel computing



Case study: Extended Kalman filter



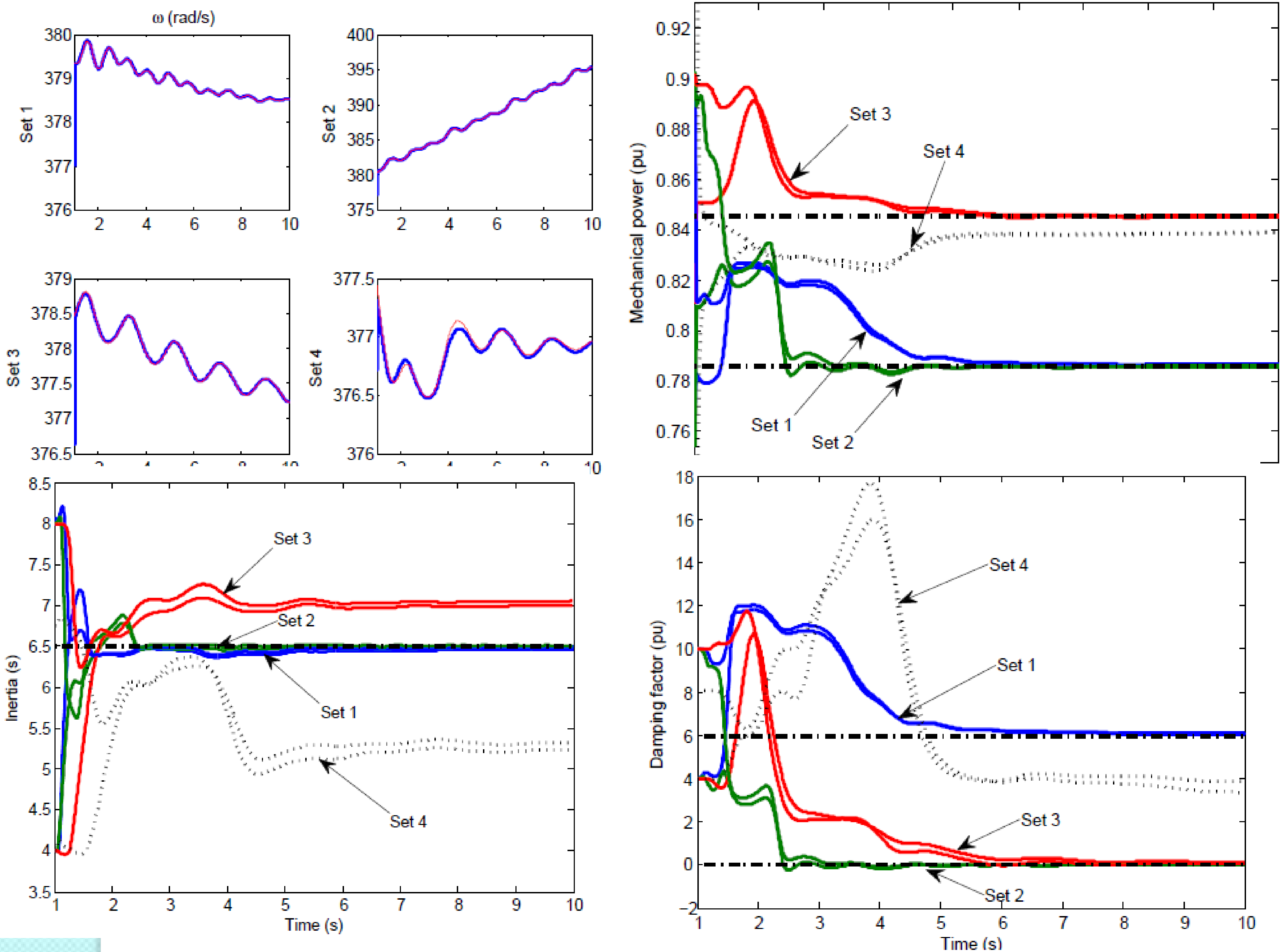


Red: classical generator models

Blue: In the second set, the damping is reduced to zero in the swing equation.

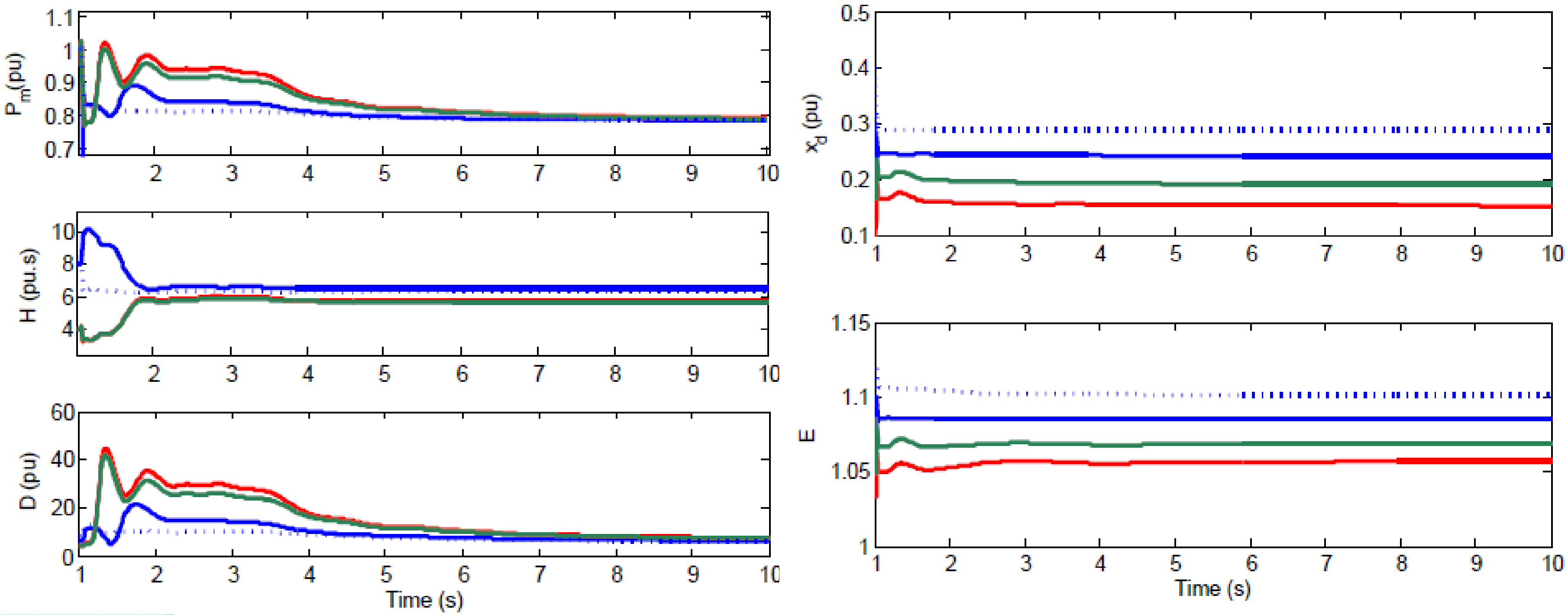
Black: In the third set, subtransient generator model is used. D=0

Magenta: In the fourth set, subtransient generator model is used. D=6. AVR enabled



ω (rad/s)
Set 1
Set 2
Set 3
Set 4
Mechanical power (pu)
Set 3
Set 4
Set 1
Set 2
Inertia (s)
Time (s)
Set 3
Set 2
Set 1
Set 4
Damping factor (pu)
Time (s)
Set 4
Set 1
Set 3
Set 2

Estimation 2



Different initial condition ➔ different converged E and x'd
5 parameter estimation is not feasible

Questions?

- Thank you!
- Contact linglingfan@usf.edu.