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

Dynamic State estimation (observer, Kalman filter)

- Known: 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 *electromagnetic* transient (resistance and inductances of armature winding, field resistance, magnetizing inductance)

- Sampling rate (many samples per cycle)

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

\[
\begin{bmatrix}
\Delta \delta \\
\Delta \omega
\end{bmatrix} =
\begin{bmatrix}
0 & \omega_0 \\
0 & -D \\
\end{bmatrix}
\begin{bmatrix}
\Delta \delta \\
\Delta \omega
\end{bmatrix} +
\begin{bmatrix}
0 & 0 \\
-1 & 0 \\
\end{bmatrix}
\begin{bmatrix}
\Delta P \\
\Delta Q
\end{bmatrix}
\]

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

\[
\hat{x}_{k+1} = A_k \hat{x}_k + B_k u_k + w_k \\
\hat{y}_{k+1} = C_{k+1} \hat{x}_{k+1} + D_{k+1} u_{k+1} + v_k
\]

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:

\[
G_k (y_{k+1} - C \hat{x}_{k+1}^- - D u_{k+1})
\]

3. update prediction:

\[
\hat{x}_{k+1} = \hat{x}_k^- + G_k (y_{k+1} - C \hat{x}_{k+1}^- - D u_{k+1})
\]
Model decoupling

Reduce estimation model
Estimate a subsystem a time

Measurement: \((V, \theta, P_e, Q_e)\)

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

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

- Thank you!

- Contact linglingfan@usf.edu.