

Secure Dynamic State Estimation Using PMU data under Model Uncertainty and Cyber Attacks

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Funded by DOE Cybersecurity of Energy Delivery Systems (CEDDS)

March 24, 2016

Outline

- 1 Dynamic State Estimation
- 2 Challenges
- 3 Estimation Approaches
- 4 Case Studies
- 5 Conclusion



Dynamic State Estimation

- ▶ Discrete-time nonlinear system

$$\begin{cases} \mathbf{x}_k = \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}) + \mathbf{q}_{k-1} \\ \mathbf{y}_k = \mathbf{h}(\mathbf{x}_k, \mathbf{u}_{k-1}) + \mathbf{r}_k \end{cases}$$

- ▶ Dynamic state estimation:

given \mathbf{x}_{k-1} and \mathbf{y}_k , estimate \mathbf{x}_k

- ▶ For power systems:
 - ▶ \mathbf{x} : internal states of generators
 - ▶ \mathbf{y} comes from synchrophasors



Challenge 1: Model Uncertainty

- ▶ Power system model can be inaccurate

- ▶ unknown inputs

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u} + \mathbf{B}_w\mathbf{w} + \phi(\mathbf{x}, \mathbf{u})$$

- ▶ unavailable inputs (not measured or difficult to measure)
 - ▶ parameter inaccuracy
- ▶ Are more detailed models always better?
 - ▶ difficult to validate and calibrate
 - ▶ higher computational burden



Challenge 2: Cyber Attacks against PMU Measurements

- ▶ National Electric Sector Cybersecurity Organization Resource (NESCOR) failure scenarios
 - ▶ measurement data compromised due to PDC authentication compromise
 - ▶ communications compromised between PMUs and control center
- ▶ Different types of attacks against measurements
 - ▶ data integrity attack
 - ▶ denial of service attack
 - ▶ replay attack



Kalman Filters

- ▶ **Extended Kalman Filter**
 - ▶ used for linearized model
 - ▶ need to calculate Jacobian
- ▶ **Unscented Kalman Filter**
 - ▶ used for nonlinear model
 - ▶ no need to calculate Jacobian
 - ▶ numerical stability problem
- ▶ **Cubature Kalman Filter**
 - ▶ used for nonlinear model
 - ▶ large system with high nonlinearity
 - ▶ better numerical stability



Dynamic Observers

- ▶ Real system dynamics

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u} + \mathbf{B}_w\mathbf{w} + \phi(\mathbf{x}, \mathbf{u})$$

- ▶ Observer dynamics

$$\dot{\hat{\mathbf{x}}} = \mathbf{A}\hat{\mathbf{x}} + \mathbf{B}\mathbf{u} + \phi(\hat{\mathbf{x}}, \mathbf{u}) + \mathbf{L}(\mathbf{y} - \mathbf{h}(\hat{\mathbf{x}}))$$

- ▶ Observer design

$$\begin{bmatrix} \mathbf{A}^\top \mathbf{P} + \mathbf{P}\mathbf{A} + (\epsilon_1 \rho + \epsilon_2 \mu) \mathbf{I}_n - \sigma \mathbf{C}^\top \mathbf{C} & \mathbf{P} + \frac{\varphi \epsilon_2 - \epsilon_1}{2} \mathbf{I}_n \\ \left(\mathbf{P} + \frac{\varphi \epsilon_2 - \epsilon_1}{2} \mathbf{I}_n \right)^\top & -\epsilon_2 \mathbf{I}_n \end{bmatrix} < 0$$

$$\mathbf{L} = \frac{\sigma}{2} \mathbf{P}^{-1} \mathbf{C}^\top$$

A Realistic Scenario for Dynamic State Estimation

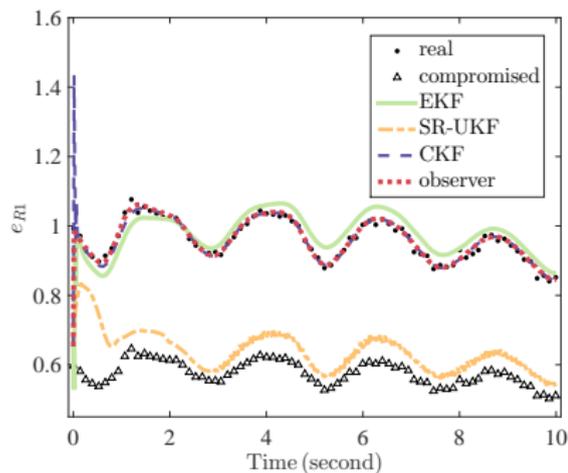
- ▶ 16-machine 68-bus system
- ▶ Power system is modeled as 10th order nonlinear system
- ▶ Gaussian Process noise and measurement noise
- ▶ Model uncertainty
 - ▶ unknown $B_w w$

$$w(t) = \begin{bmatrix} 0.5 \cos(\omega_u t) \\ 0.5 \sin(\omega_u t) \\ 0.5 \cos(\omega_u t) \\ 0.5 \sin(\omega_u t) \\ -e^{-5t} \\ 0.2 e^{-t} \cos(\omega_u t) \\ 0.2 \cos(\omega_u t) \\ 0.1 \sin(\omega_u t) \end{bmatrix}$$

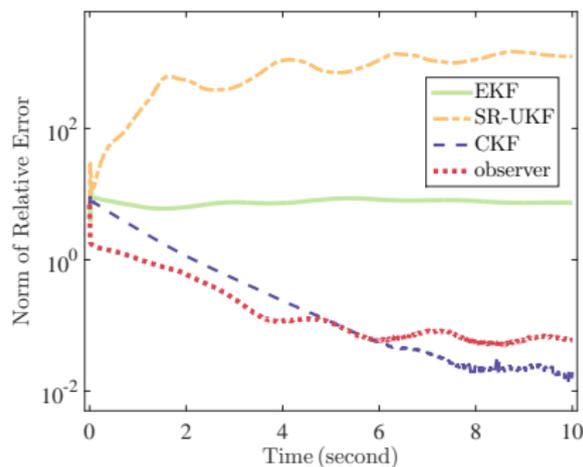
- ▶ estimator only knows steady-state values of T_m and E_{fd}
 - ▶ reduced admittance matrix is the steady-state one within 1 second after fault
- ▶ Initial guess of the states is far from the real states

Data Integrity Attack

Data integrity attack: 8 out of 64 measurements are scaled by k or $1/k$
($k = 0.6$)



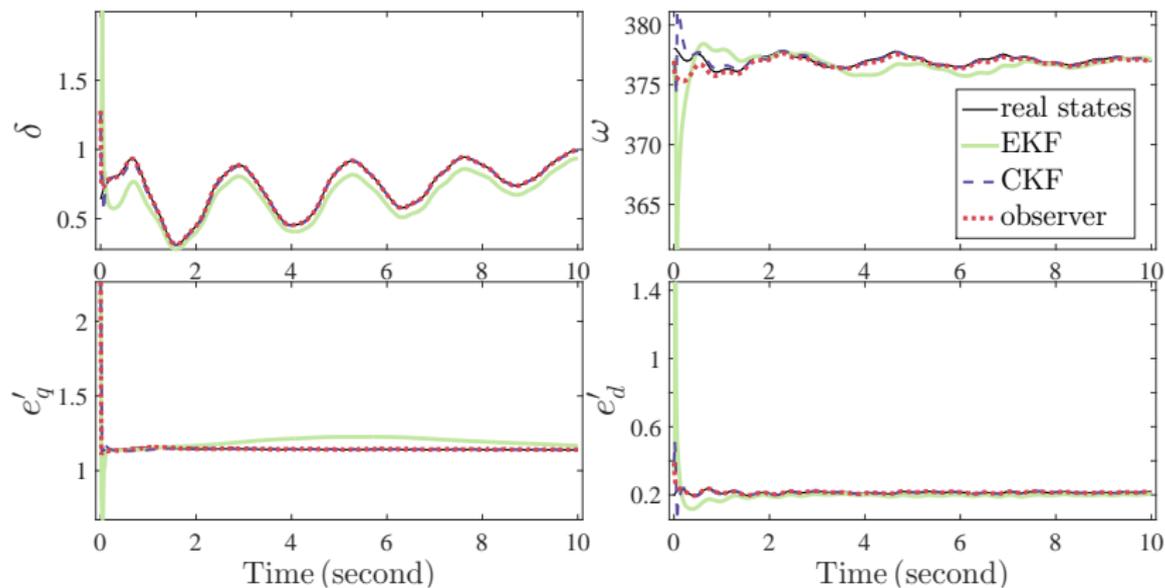
Compromised measurements e_{R1}



Norm of relative error of states



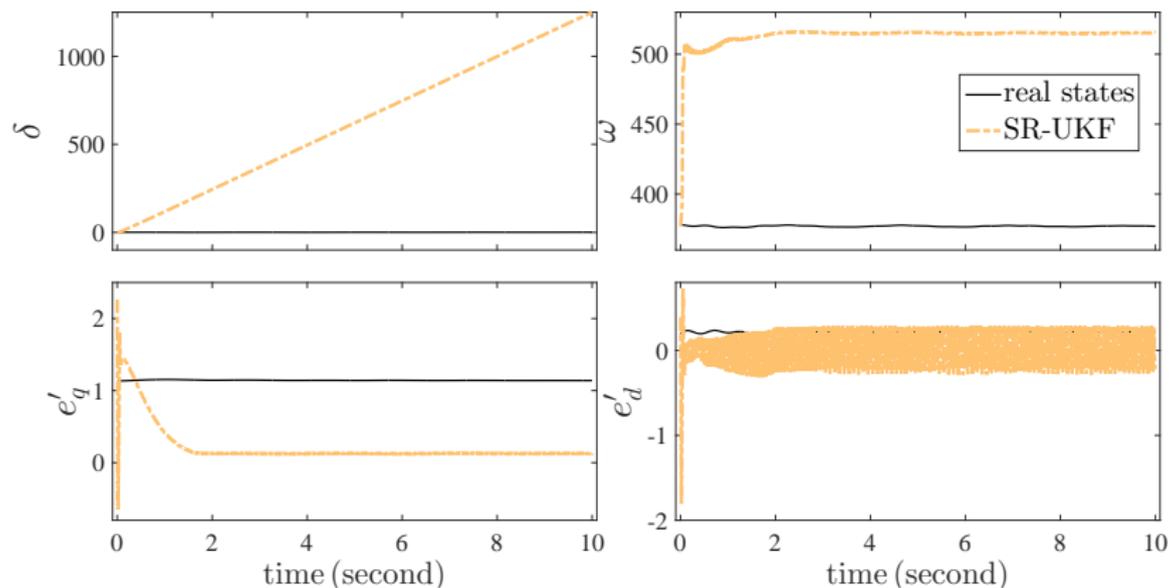
Data Integrity Attack (cont'd)



Estimation from EKF, CKF, and observer



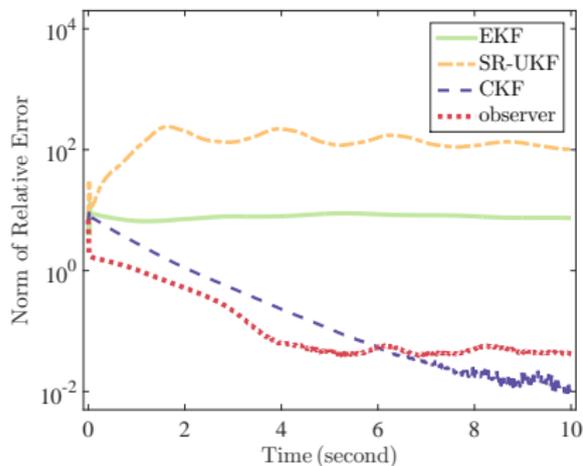
Data Integrity Attack (cont'd)



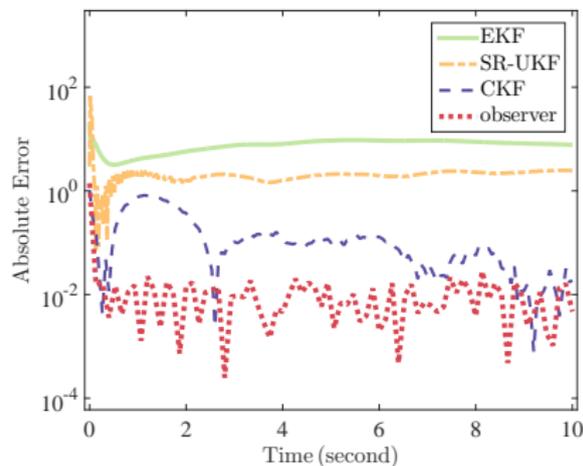
Estimation from SR-UKF

Denial of Service Attack

8 measurements do not update for $t \in [3s, 6s]$



Norm of relative error of states

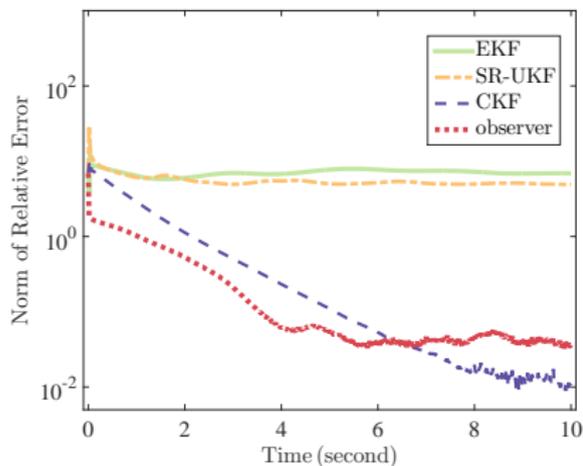


Absolute error of measurements

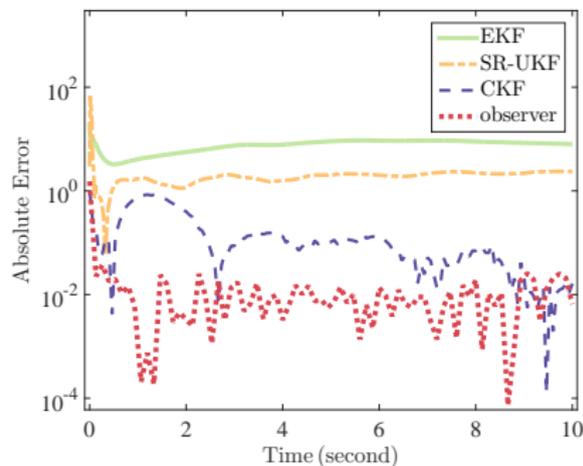


Replay Attack

8 measurements for $t \in [3s, 6s]$ equal those $t \in [0s, 3s]$



Norm of relative error of states



Absolute error of measurements



Conclusion

- ▶ We design a realistic scenario for DSE with significant model uncertainty and cyber attacks
- ▶ We compare different estimation approaches
 - ▶ observers are more robust to model uncertainty and cyber attacks
 - ▶ observers have theoretical guarantee for convergence
 - ▶ observers are easier to implement



References

- ▶ J. Qi, A. F. Taha, and J. Wang, “Comparing Kalman filters and observers for dynamic state estimation with model uncertainty and malicious cyber attacks,” *IEEE Trans. Power Systems*, under review.
- ▶ A. F. Taha, J. Qi, J. Wang, and J. H. Panchal, “Risk mitigation for dynamic state estimation against cyber attacks and unknown inputs,” *IEEE Trans. Smart Grid*, under review.
- ▶ J. Qi and K. Sun, J. Wang, and H. Liu, “Dynamic state estimation for multi-machine power system by unscented Kalman filter with enhanced numerical stability,” *IEEE Trans. Smart Grid*, under review.
- ▶ K. Sun, J. Qi, and W. Kang, “Power system observability and dynamic state estimation for stability monitoring using synchrophasor measurements,” *Control Engineering Practice*, in press.
- ▶ J. Qi, K. Sun, and W. Kang, “Adaptive optimal PMU placement based on empirical observability gramian,” *IFAC NOLCOS 2016*, under review.
- ▶ J. Qi, K. Sun, and W. Kang, “Optimal PMU placement for power system dynamic state estimation by using empirical observability gramian,” *IEEE Trans. Power Systems*, vol. 30, no. 4, pp. 2041–2054, Jul. 2015.
- ▶ W. Zhang, H. Su, H. Wang, and Z. Han, “Full-order and reduced-order observers for one-sided lipschitz nonlinear systems using riccati equations,” *Commun. Nonlinear Sci. Numer. Simul.*, vol. 17, no. 12, pp. 4968–4977, 2012.

THANK YOU!

