



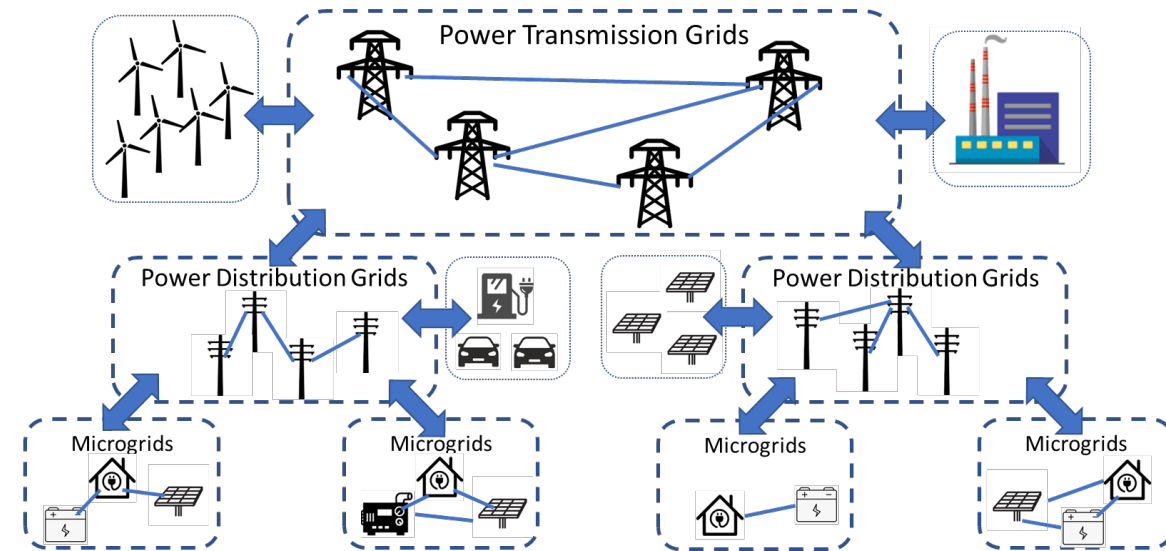
# State and Parameter Estimation for Inverter-Based Resources

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# Inverter Based Resources (IBRs)

- Future power grids will be dominated by devices with power-electronics interfaces, i.e., inverter-based resources.
- **Challenges on power system dynamics:**
  - Low inertia and fast dynamics;
  - Distributed and diverse controls;
  - New instability mechanisms (DC side, PLL, etc.);
  - Stability issues over wide frequency range.
- Power grids require more advanced monitoring technologies to provide support for real-time decision-making.



Power grid dominated by inverter-based resources (IBRs).

# Dynamic State Estimation (DSE)

- Dynamic state estimation (DSE) emerges as a power tool for the monitoring of power system dynamics [1].
- Over the past decade, extensive work has been done of the DSE of synchronous generators (SGs).
- Comparatively, much less has been accomplished on the DSE of IBRs.
- **As SGs are gradually replaced by IBRs, IBRs need to be monitored in a similar way as SGs.** Not much consensus has been reached on DSE for IBRs.

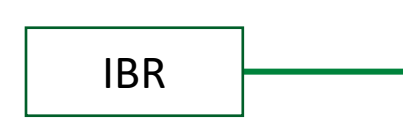


$$\dot{\delta} = \omega - \omega_0$$

$$\frac{H}{\pi f_0} \dot{\omega} = P_M - P_e - D(\omega - \omega_0) / \omega_0$$

$$T'_{do} \dot{E}'_q = -E'_q - (X_d - X'_d)I_d + E_{fd}$$

$$T'_{qo} \dot{E}'_d = -E'_d + (X_q - X'_q)I_q$$



?

Dynamics of SGs vs. dynamics of IBRs.

# DSE for IBRs: Motivation

- DSE for IBRs can enable a variety of novel applications. A few examples are given below.
  - **Modeling:**

**Example:** T. Wang, S. Huang, M. Gao and Z. Wang, "Adaptive extended Kalman filter based dynamic equivalent method of PMSG wind farm cluster," IEEE Transactions on Industry Applications, vol. 57, no. 3, pp. 2908-2917, May-June 2021.
  - **Monitoring:**

**Example:** K. Yue, Y. Liu, P. Zhao, B. Wang, M. Fu and H. Wang, "Dynamic state estimation enabled health indicator for parametric fault detection in switching power converters," IEEE Access, vol. 9, pp. 33224-33234, 2021.
  - **Control:**

**Example:** S. Yu, T. Fernando, K. Emami and H. H. -C. Lu, "Dynamic state estimation based control strategy for DFIG wind turbine connected to complex power systems," IEEE Transactions on Power Systems, vol. 32, no. 2, pp. 1272-1281.
  - **Protection:**

**Example:** Kaiyu Liu, Dynamic State Estimation Based Protection for Power Electronics Systems, Ph.D. Dissertation, Georgia Institute of Technology, 2022.

# DSE for IBRs: Available Measurements

- Possible data sources for DSE for IBRs are summarized as below.

Measurements [2]	Synchronization	Continuity	Sampling Rate	Dynamics to capture
SCADA	non-synchronized	continuous remotely	$\sim 10^0$ samples per sec	Steady state
Phasor measurement units (PMUs) and micro-PMUs	synchronized	continuous remotely	$\sim 10^1$ - $10^2$ samples per sec	Outer-loop control; electromechanics
Dynamic disturbance recorders (DDRs) [2]	synchronized	continuous remotely	$\sim 10^1$ - $10^2$ samples per sec	Outer-loop control; electromechanics
Waveform measurement units (WMUs) [3]	synchronized	continuous remotely	$\sim 10^2$ - $10^3$ samples per sec	Outer-loop/inner-loop control; electromechanics/electromagnetics
Merging units (MUs) and Digital fault recorders (DFRs)	synchronized /non-synchronized	continuous locally; event-triggered remotely	$\sim 10^3$ - $10^4$ samples per sec	Inner-loop control; electromagnetics
Inverter sensors	non-synchronized	continuous locally; event-triggered remotely	$\sim 10^4$ - $10^5$ samples per sec	Inner-loop control; electromagnetics; high-frequency transients

- Edge computing technologies can be exploited to perform **local** DSE for IBRs (with local applications plus down-sampled reporting to control centers for grid-wise applications).

[2] NERC Reliability Guideline, BPS-Connected Inverter-Based Resource Performance, Sep. 2018. [https://www.nerc.com/comm/PC\\_Reliability\\_Guidelines\\_DL/Inverter-Based\\_Resource\\_Performance\\_Guideline.pdf](https://www.nerc.com/comm/PC_Reliability_Guidelines_DL/Inverter-Based_Resource_Performance_Guideline.pdf)

[3] M. Izadi and H. Mohsenian-Rad, "Synchronous Waveform Measurements to Locate Transient Events and Incipient Faults in Power Distribution Networks," in IEEE Transactions on Smart Grid, vol. 12, no. 5, pp. 4295-4307, Sept. 2021.

# DSE for IBRs: Existing Works and Limitations

- Existing work on DSE for IBRs:
  - Systems: DFIG-WT, PMSG-WT, solar PV, energy storage, microgrid
  - Algorithms: IEKF, AEKF, UKF, EnKF, ACKF, UPF, ...
- Essential difference from SG: IBR dynamics are largely dependent by controllers, i.e., **are a heavy mix of physical and digital (cyber) dynamics!**
- Limitations of existing work: physical plant and digital controller models are blended in a single-state space.
  - Inability to address the uncertainties of data flows between the physical plant and the controller (i.e., uncertainties in measurement signals and control signals).
  - Inability to distinguish between cyber and physical events.
  - Inability to adapt to diverse control algorithms and control mode switching.

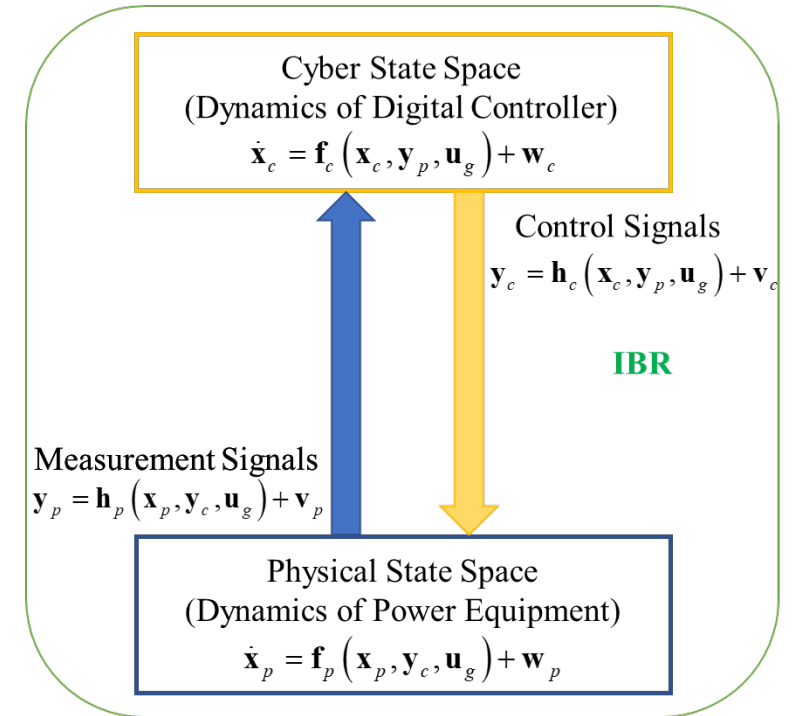
**Conventional Single state-space model of an IBR**

$$\frac{d(\mathbf{x})}{dt} = \mathbf{f}(\mathbf{x}, \mathbf{u}_g) + \mathbf{w},$$

$$\mathbf{y} = \mathbf{h}(\mathbf{x}, \mathbf{u}_g) + \mathbf{v}.$$

# Cyber-Physical State-Space Representation of IBRs

- We propose a dual cyber-physical state-space model for IBRs, where the interaction between physical dynamics and digital (cyber) dynamics can be explicitly modeled.
- Strength of the proposed model:
  - Modeling and suppressing the uncertainties in measurement signals and control signals.
  - Ability to distinguish between cyber and physical events.
  - Versatility to diverse control algorithms and control mode switching.



Cyber-physical state-space representation of IBRs.

**Proposed**

$$\frac{d(\mathbf{x}_p)}{dt} = \mathbf{f}_p\left(\mathbf{x}_p, \underbrace{\mathbf{h}_c(\mathbf{x}_c, \mathbf{y}_p, \mathbf{u}_g) + \mathbf{v}_c}_{\mathbf{y}_c}, \mathbf{u}_g\right) + \mathbf{w}_p,$$

$$\frac{d(\mathbf{x}_c)}{dt} = \mathbf{f}_c\left(\mathbf{x}_c, \underbrace{\mathbf{h}_p(\mathbf{x}_p, \mathbf{y}_c, \mathbf{u}_g) + \mathbf{v}_p}_{\mathbf{y}_p}, \mathbf{u}_g\right) + \mathbf{w}_c.$$

**Conventional**

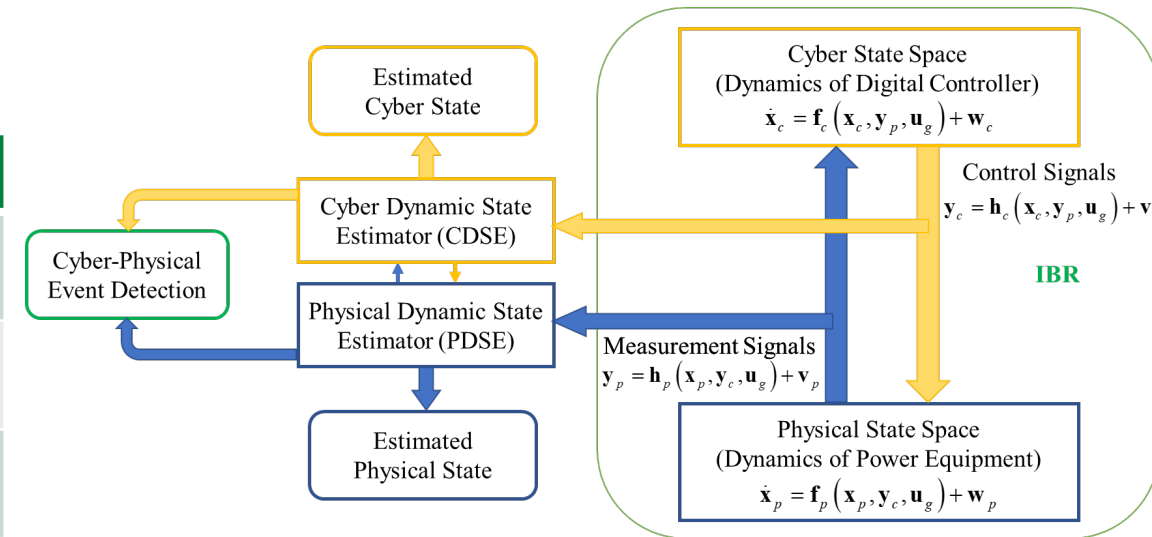
$$\frac{d(\mathbf{x}_p)}{dt} = \mathbf{f}'_p(\mathbf{x}_p, \mathbf{x}_c, \mathbf{u}_g) + \mathbf{w}'_p,$$

$$\frac{d(\mathbf{x}_c)}{dt} = \mathbf{f}'_c(\mathbf{x}_c, \mathbf{x}_p, \mathbf{u}_g) + \mathbf{w}'_c,$$

# Cyber-Physical Dual DSE for IBRs

- Noting the duality of the cyber state space and the physical state space, a dual DSE framework can be constructed.

	Physical DSE (PDSE)	Cyber DSE (CDSE)
Observations	Measurement signals	Control signals
States to track	Physical states of circuits, machines, batteries, etc.	Digital states of controllers
Errors to filter	Noise and bad data in measurement signals	Noise and bad data in control signals
Events to detect	Physical events (faults, switching, etc.)	Cyber events (controller failure, cyber attacks, etc.)
Parameters to identify	Physical parameters (inductance, inertia, etc.)	Control parameters (PI gain, droop, etc.)



Cyber-physical dual DSE framework for IBRs.

- The framework is generic. Any existing DSE algorithm can be applied, e.g., EKF, UKF, CKF, etc.



# Physical State Space of IBRs: Solar PV System Example

- State equations:

$$\frac{d(V_{dc})}{dt} = \frac{1}{C_{dc}V_{dc}}(V_{dc}I_{dc}^z - V_{iq}^c I_{iq} - V_{id}^c I_{id}) + V_{dc}^w,$$

$$\frac{d(I_{id})}{dt} = \frac{1}{L_i}(V_{id}^c - R_i I_{id} - V_{cd} - \hat{\omega} L_i I_{iq}) + I_{id}^w,$$

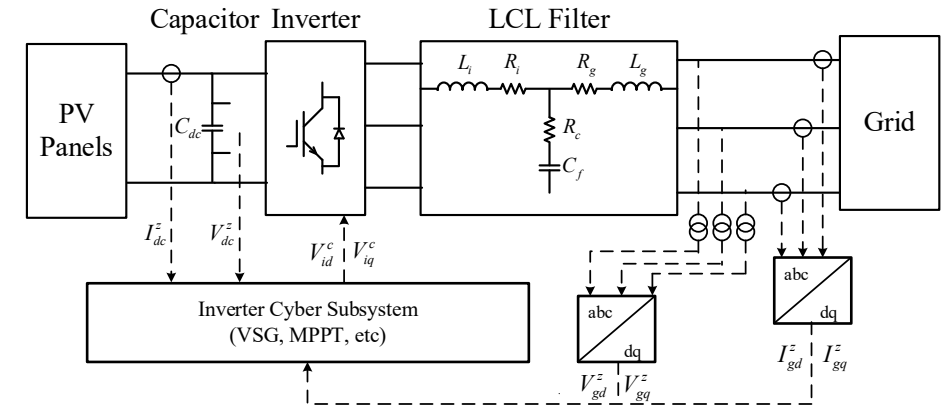
$$\frac{d(I_{iq})}{dt} = \frac{1}{L_i}(V_{iq}^c - R_i I_{iq} - V_{cq} - \omega_g^{ex} L_i I_{id}) + I_{iq}^w,$$

$$\frac{d(I_{gd})}{dt} = \frac{1}{L_g}(V_{cd} - R_g I_{gd} - V_{gd}^z + \omega_g^{ex} L_g I_{gq}) + I_{gd}^w,$$

$$\frac{d(I_{gq})}{dt} = \frac{1}{L_g}(V_{cq} - R_g I_{gq} - V_{gq}^z - \omega_g^{ex} L_g I_{gd}) + I_{gq}^w,$$

$$\frac{d(V_{cd})}{dt} = -\left(\frac{R_c}{L_i} + \frac{R_c}{L_g}\right)V_{cd} + \left(\frac{1}{C_f} - \frac{R_c}{L_i}R_i\right)I_{id} - \left(\frac{1}{C_f} - \frac{R_c}{L_g}R_g\right)I_{gd} + \frac{R_c}{L_i}V_{id}^c + \frac{R_c}{L_g}V_{gd}^z + \omega_g^{ex}V_{cq} + V_{cd}^w,$$

$$\frac{d(V_{cq})}{dt} = -\left(\frac{R_c}{L_i} + \frac{R_c}{L_g}\right)V_{cq} + \left(\frac{1}{C_f} - \frac{R_c}{L_i}R_i\right)I_{iq} - \left(\frac{1}{C_f} - \frac{R_c}{L_g}R_g\right)I_{gq} + \frac{R_c}{L_i}V_{iq}^c + \frac{R_c}{L_g}V_{gq}^z - \omega_g^{ex}V_{cd} + V_{cq}^w.$$



Solar PV generation system.

- Output equations:

$$I_{gd}^z = I_{gd} + I_{gd}^v,$$

$$I_{gq}^z = I_{gq} + I_{gq}^v,$$

$$V_{dc}^z = V_{dc} + V_{dc}^v.$$

# Cyber State Space of IBRs: Grid-Following Control Example (MPPT)

- State equations:

$$\frac{d(M_1)}{dt} = k_{i1} (V_{dc}^z - g(V_{dc}^z, I_{dc}^{ex})) + M_1^w,$$

$$\frac{d(M_2)}{dt} = k_{i2} \left( (M_1 + k_{p1} (V_{dc}^z - g(V_{dc}^z, I_{dc}^{ex}))) - I_{gd}^z \right) + M_2^w,$$

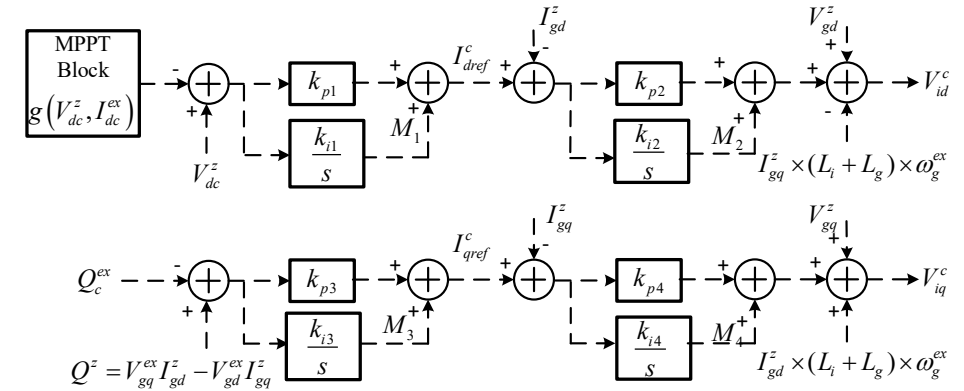
$$\frac{d(M_3)}{dt} = k_{i3} (V_{gq}^{ex} I_{gd}^z - V_{gd}^{ex} I_{gq}^z - Q_c^{ex}) + M_3^w,$$

$$\frac{d(M_4)}{dt} = k_{i4} (M_3 - I_{gq}^z + k_{p3} (V_{gq}^{ex} I_{gd}^z - V_{gd}^{ex} I_{gq}^z - Q_c^{ex})) + M_4^w.$$

- Output equations:

$$V_{id}^c = V_{gd}^{ex} - I_{gq}^z (L_i + L_g) \omega_g^{ex} + M_2 + k_{p2} (M_1 + k_{p1} (V_{dc}^z - g(V_{dc}^z, I_{dc}^{ex}))) - I_{gd}^z + V_{id}^v,$$

$$V_{iq}^c = V_{gq}^{ex} + I_{gd}^z (L_i + L_g) \omega_g^{ex} + M_4 + k_{p4} (M_3 + k_{p3} (V_{gq}^{ex} I_{gd}^z - V_{gd}^{ex} I_{gq}^z - Q_c^{ex})) - I_{gq}^z + V_{iq}^v.$$



Maximum Power Point Tracking (MPPT) control for solar PV systems.

# Cyber State Space of IBRs: Grid-Forming Control Example (VSG)

- State equations:

$$\frac{d(P_{set})}{dt} = \frac{-k_{gp}(\omega_g^{ex} - \omega_0) - (P_{set} - P_0)}{T_d} + P_{set}^w,$$

$$\frac{d(\omega)}{dt} = \frac{1}{J} \left( \frac{P_{set}}{\omega} + D_p(\omega_g^{ex} - \omega) - \frac{V_{gd}^{ex} I_{gd}^z + V_{gq}^{ex} I_{gq}^z}{\omega} \right) + \omega^w,$$

$$\frac{d(\Delta\theta)}{dt} = \omega - \omega_g^{ex} + \Delta\theta^w,$$

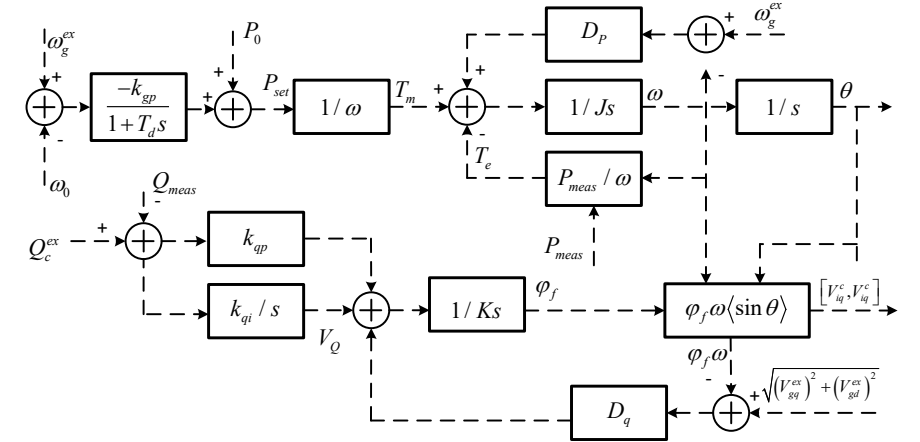
$$\frac{d(V_Q)}{dt} = k_{qi} \left( Q_c^{ex} - (V_{gq}^{ex} I_{gd}^z - V_{gd}^{ex} I_{gq}^z) \right) + V_Q^w,$$

$$\frac{d(\varphi_f)}{dt} = \frac{1}{K} \left( k_{qp} \left( Q_c^{ex} - (V_{gq}^{ex} I_{gd}^z - V_{gd}^{ex} I_{gq}^z) \right) + V_Q + D_q \left( \sqrt{(V_{gq}^{ex})^2 + (V_{gd}^{ex})^2} - \varphi_f \omega \right) \right) + \varphi_f^w.$$

- Output equations:

$$V_{id}^c = \omega \varphi_f \cos(\Delta\theta) + V_{id}^v,$$

$$V_{iq}^c = \omega \varphi_f \sin(\Delta\theta) + V_{iq}^v.$$



Virtual Synchronous Generator (VSG) control.

# Dynamic Parameter Estimation (DPE) of IBRs

- Motivation: With growing penetration of IBRs, the dynamic models of IBRs must be accurate enough for characterizing behaviors of the system under disturbances.
- Common reasons for inaccurate model parameters:
  - Inaccurate plant equivalent models by manufacturers
  - Physical model parameters: change of ambient condition, change of operating point, etc.
  - Controller model parameters: unreported tuning, commend from higher-level control, etc. For example, “inertia constant” and “damping coefficient” of a VSG can be easily modified!
- By state augmentation, DSE algorithms can be easily extended to track either physical or controller model parameters.

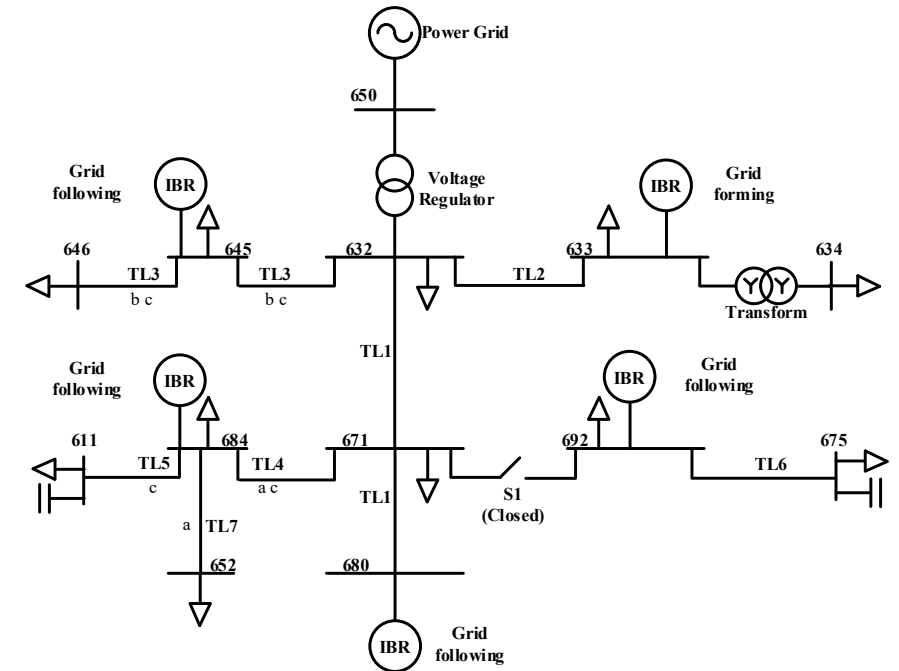
$$\tilde{\mathbf{x}}_{\phi} = (\mathbf{x}_{\phi}^T, \mathbf{p}_{\phi}^T)^T ;$$

$$\frac{d(\tilde{\mathbf{x}}_{\phi})}{dt} = \begin{cases} \frac{d(\mathbf{x}_{\phi})}{dt} = f(\mathbf{x}_{\phi}, \mathbf{y}_{\bar{\phi}}, \mathbf{u}_g), \\ \frac{d(\mathbf{p}_{\phi})}{dt} = \mathbf{1}, \end{cases}$$

$$\phi \in \{c, p\}; \bar{\phi} = \{c, p\} \setminus \phi.$$

# Case Study

- Simulation is performed on IEEE 13-node test feeder. 5 solar PV systems are integrated:
  - IBRs at nodes 645 & 684: single-phase, 50 kVA, MPPT;
  - IBRs at nodes 680 & 692: three-phase, 500 kVA, MPPT;
  - IBR at node 633: three-phase, 500kVA, VSG.
- DSE is performed for the IBR at node 692 (grid-following, MPPT) and the IBR at node 633 (grid-forming, VSG).
- Cubature Kalman filter (CKF) is used for noise filtering and the largest normalized residual (LNR) test is used for bad data processing.
- True values are generated via Simulink.
- Measurement sampling rate is 3840Hz. MU, DFR, or inverter sensors can readily fulfill this requirement.



IEEE 13-node test feeder with 5 IBRs.

# Case Study

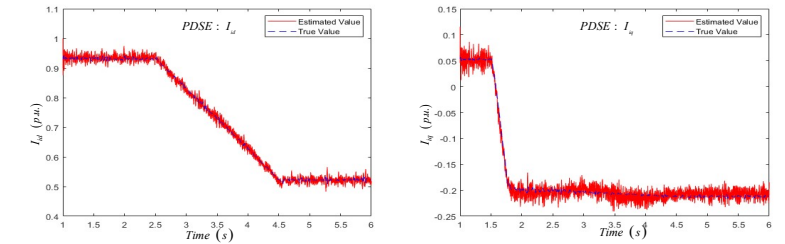
- For the grid-following (MPPT) controlled IBR, a reactive power reference change is implemented at 1.5s, and a solar irradiance change is implemented at 2s.
- The DSEs track the states of both the physical system and the controller very well.
- The RMSEs of the estimated outputs (i.e., measurement signals and control signals) are significantly lower than those of the raw outputs, validating the noise filtering effect of the estimators.

RMSE of physical system output.

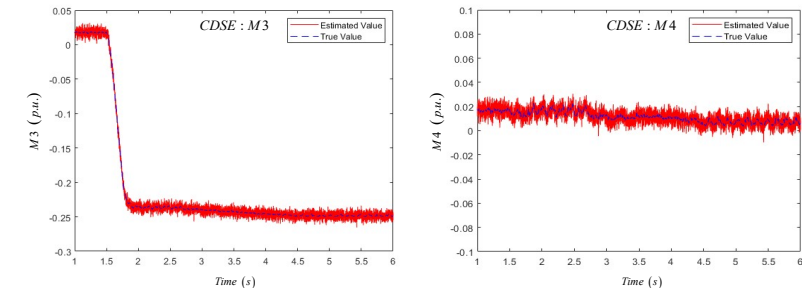
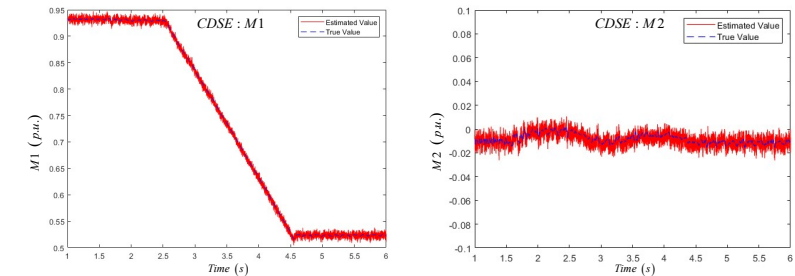
	$I_{gd}^z$	$I_{gq}^z$	$V_{dc}^z$
Raw	2.00%	2.00%	2.00%
Estimated	0.68%	0.62%	0.31%

RMSE of cyber system output.

	$V_{id}^c$	$V_{iq}^c$
Raw	2.00%	2.00%
Estimated	0.68%	0.62%



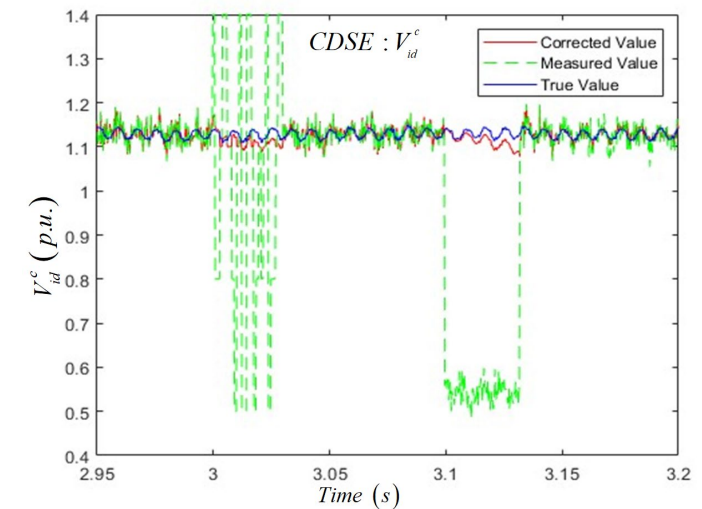
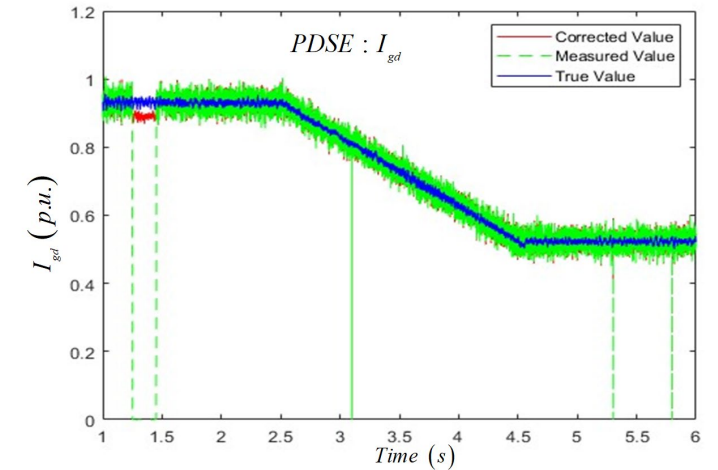
Tracking of physical PV system state.



Tracking of grid-following (MPPT) controller state.

# Case Study

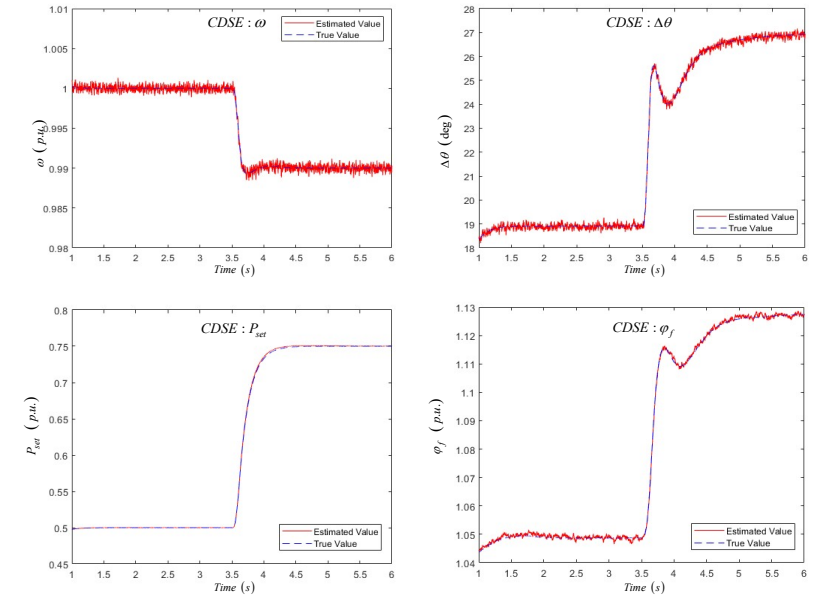
- Bad data are added into both measurement signals and control signals.
  - Measurement signals (outputs of physical system): sensor poor contact, communication packet losses.
  - Control signals (outputs of digital controller): random number, signal swapping.
- Bad data in measurement signals and control signals can be effectively suppressed.



Bad data detection and suppression for grid-following (MPPT) controller.

# Case Study

- For the grid-forming (VSG) controlled IBR, a frequency droop is implemented at 3.5s.
- The DSEs track the states of both the physical system and the controller very well.
- Note that the VSG states, i.e., “**power angle**”, “**rotor speed**”, etc. are internal states of the digital controller, which are not disclosed to grid operators. However, based on the outputs of the controller, these variables can be accurately estimated, which are critical to online stability analysis of the system.



Tracking of grid-forming (VSG) controller state.

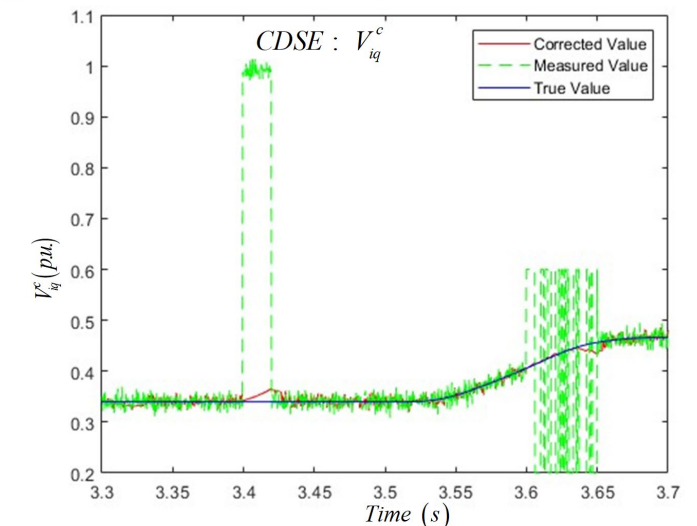
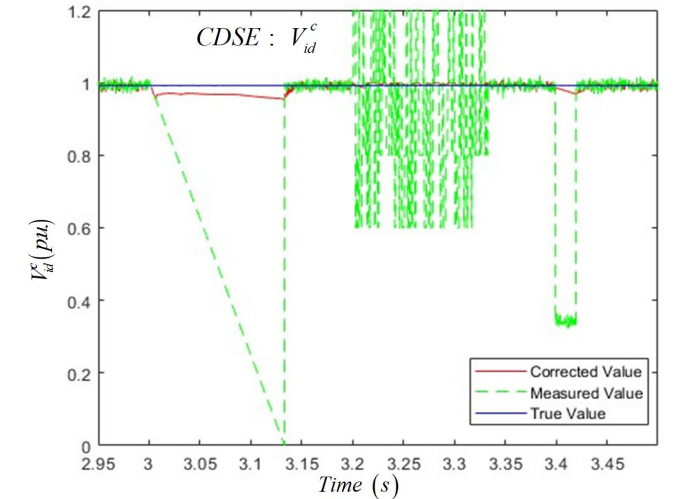
RMSE of cyber system output.

	$V_{id}^c$	$V_{iq}^c$
Raw	1.00%	1.00%
Estimated	0.09%	0.18%



# Case Study

- Bad data are added into both measurement signals and control signals.
  - Measurement signals (outputs of physical system): sensor poor contact, communication packet losses.
  - Control signals (outputs of digital controller): random number, ramp change, and step change.
- Bad data in measurement signals and control signals can be effectively suppressed.



Bad data detection and suppression for grid-forming (VSG) controller.

# Conclusion

- **DSE for IBRs** can enable various novel applications for system modeling, monitoring, control, and protection. Data sources for DSE for IBRs are reviewed.
- We present a **dual cyber-physical state space model** to characterize the heavy mix of digital and physical dynamics of IBRs. This model allows:
  - Modeling the uncertainties in measurement signals and control signals;
  - Ability to distinguish between cyber and physical events;
  - Versatility to diverse control algorithms and control mode switching.
- A **dual DSE framework** based on the cyber-physical state space model is proposed. Simulation results show that the proposed framework can:
  - Track the unknown states of the physical inverter system and the digital controller;
  - Detect/suppress bad data in measurement signals and control signals.
- The possibility of **parameter estimation** for both the physical inverter system and the digital controller is discussed.

# Publications and Acknowledgement

## Relevant Publications:

- H. Huang, **Y. Lin**, X. Lu, Y. Zhao, and A. Kumar, “Dynamic state estimation for inverter-based resources: a cyber-physical dual estimation framework,” IEEE Transactions on Smart Grid, under review.
- **Y. Lin**, Y. Liu, X. Lu, and H. Huang, “State and parameter estimation for microgrids,” Microgrids: Theory and Practice. IEEE Press, to be published in 2023.
- S. Song, H. Xiong, **Y. Lin**, M. Huang, Z. Wei, Z. Fang, "Robust three-phase state estimation for PV-integrated unbalanced distribution systems," Applied Energy. (early access)
- S. Song, P. Wu, **Y. Lin**, and Y. Chen, "A general dynamic state estimation framework for monitoring and control of permanent magnetic synchronous generators-based wind turbines," IEEE Access, vol. 9, pp. 72228-72238, 2021.
- S. Song, H. Wei, **Y. Lin**, C. Wang, and A. Gomez-Exposito, “A holistic state estimation framework for active distribution networks with battery energy storage systems,” Journal of Modern Power Systems and Clean Energy, vol. 10, no. 3, pp. 627-636, May 2022.

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- Data-Driven Anticipatory Real-Time Dynamic Security Assessment for Disturbance-Resilient Microgrids. ONR University – Navy Research Collaboration on Robust Energy Infrastructure and Resiliency. 2021-2023.
- Solar PLUS: Solar Integration through Physics-Aware Learning Based Ultra-Scalable Modeling and Analytics. DOE Solar Energy Technology Office (SETO), 2021-2023.
- Graph-Learning-Assisted State and Event Tracking for Solar-Penetrated Power Grids with Heterogeneous Data Sources. DOE Solar Energy Technology Office (SETO), 2021-2024.