RECONSTRUCTION OF GRID MEASUREMENTS IN THE PRESENCE OF ADVERSARIAL ATTACKS

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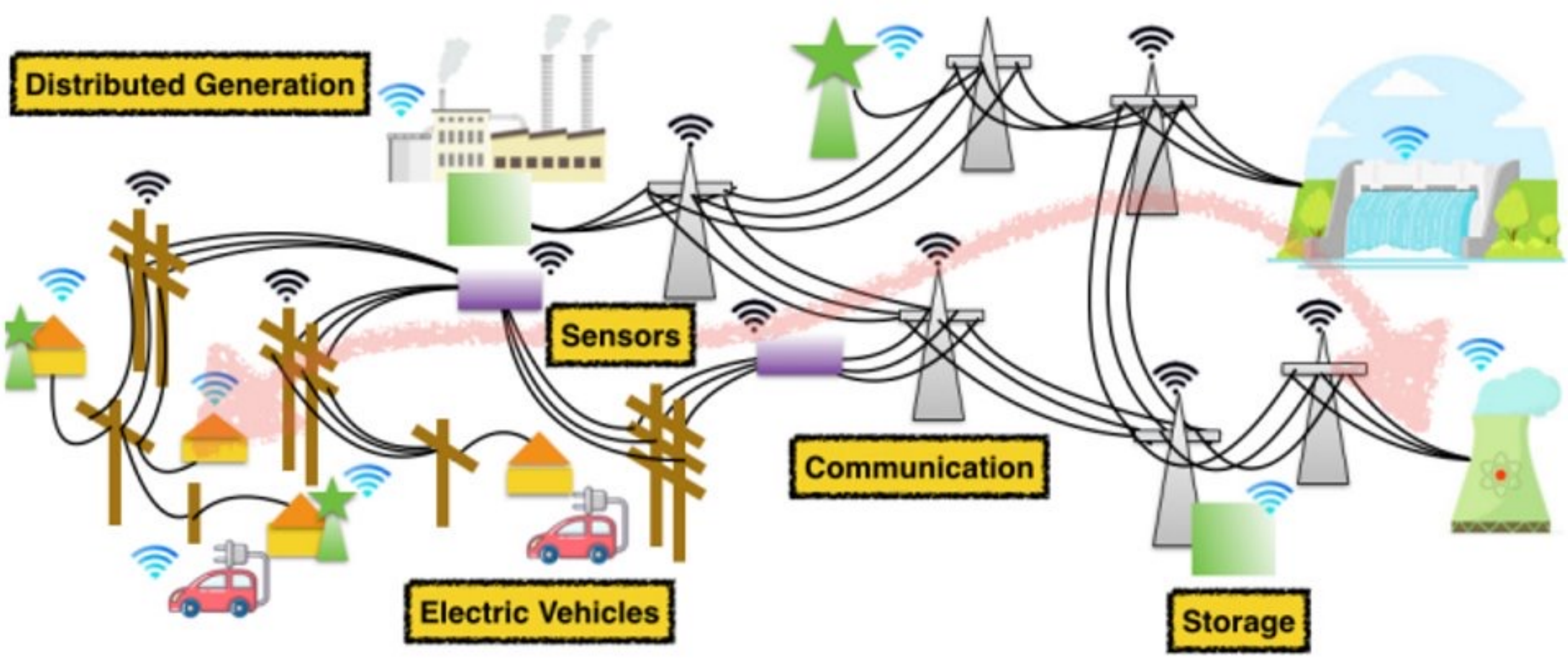
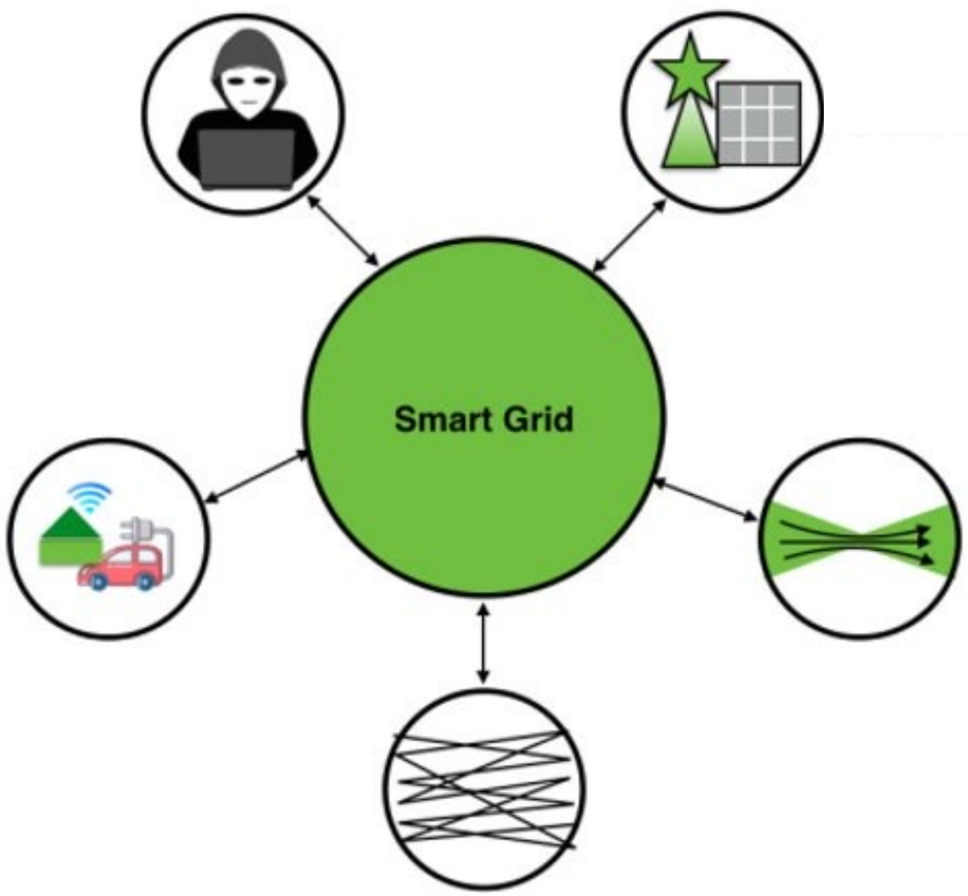
Introduction

- **Climate change:** Proliferation of highly variable renewables
- **Cyber-physical:** Vulnerabilities in the cyber plane
- **Stable operations:** Real-time monitoring resilient to cyber attacks



Motivation

- **Impact of cyber attacks on grid operation**:
  - Renewables: Introduce significant flux in the grid
  - Attacks: Increase modes of instability in the grid
- **Cyber attacks examples**:
  - 2011, Stuxnet worm Iran nuclear plant [1]
  - 2015, Ukraine blackout [2]
  - 2019, Venezuela power grid attack [3]



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Problem Statement

- **State estimation**:
  - Infer grid states (x) given a set of grid measurements (y)

$$y + \epsilon = H(x); \;\; x = H^{-1}(y + \epsilon)$$

  - Cycle GAN is used for **approximating** H and H^{-1}
- **False data injection**: Common attack in state estimation
  - Cannot detect perturbations to measurements using traditional residual checking
  - Lead to incorrect state inferences

$$x = H^{-1}(y + a + \epsilon)$$

  - Iterative gradients computed using Cycle GAN modules used for **reconstructing** perturbed measurements

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Existing Work

	No knowledge of grid structure	Unsupervised Training Dataset	Recovering from higher rates of perturbation
Proposed Method	✓	✓	✓
GAN Based method [4]	x	x	?
Numerical Method [5]	✓	N/A	?
Machine Learning [6]	x	x	✓

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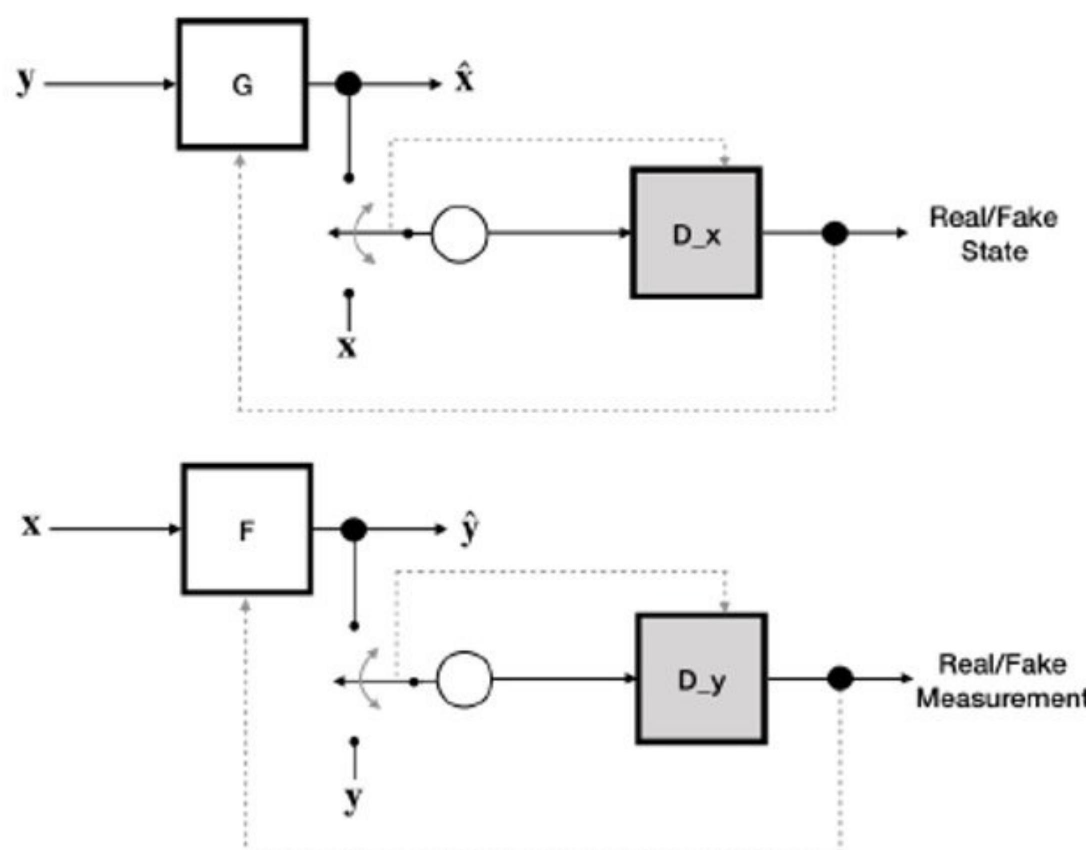
Cycle GAN

- Composed of two sets of GANs
  - Forward GAN: G is mapping from measurements to states ($G \approx H^{-1}$)
  - Reverse GAN: F is mapping from states to measurements ($F \approx H$)



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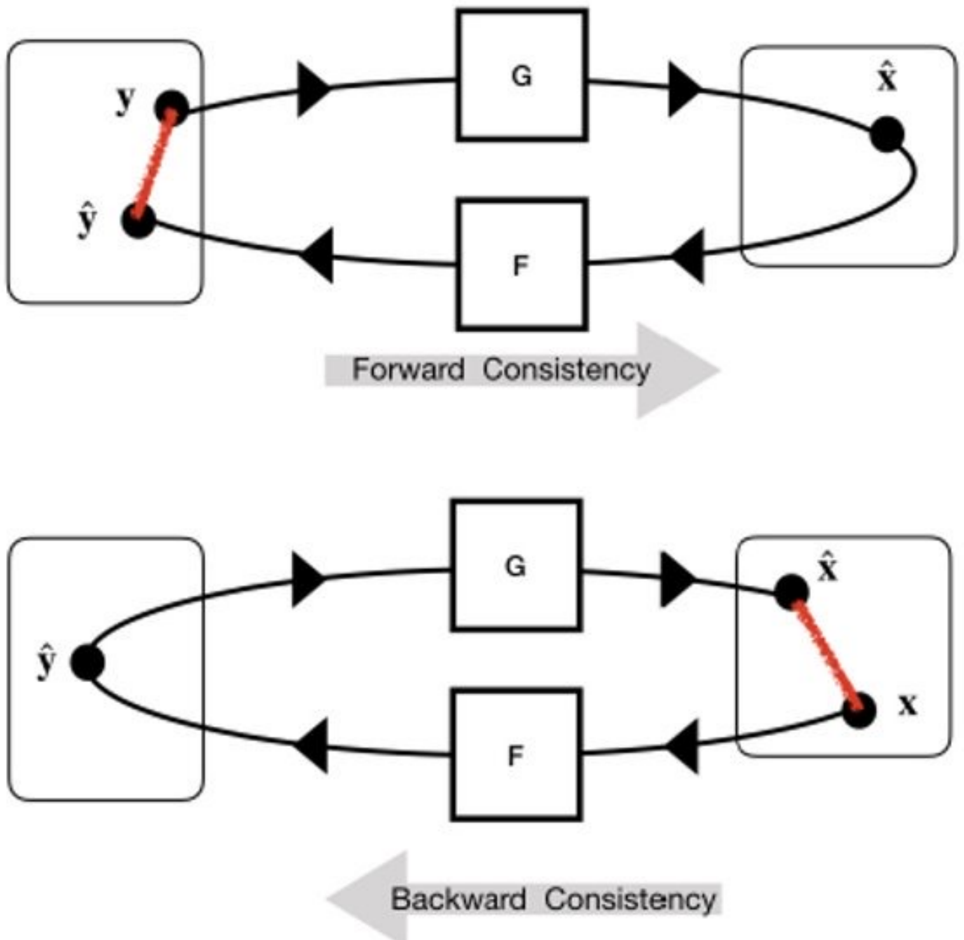
Cycle GAN

- Mapping between domains: Cycle consistency loss



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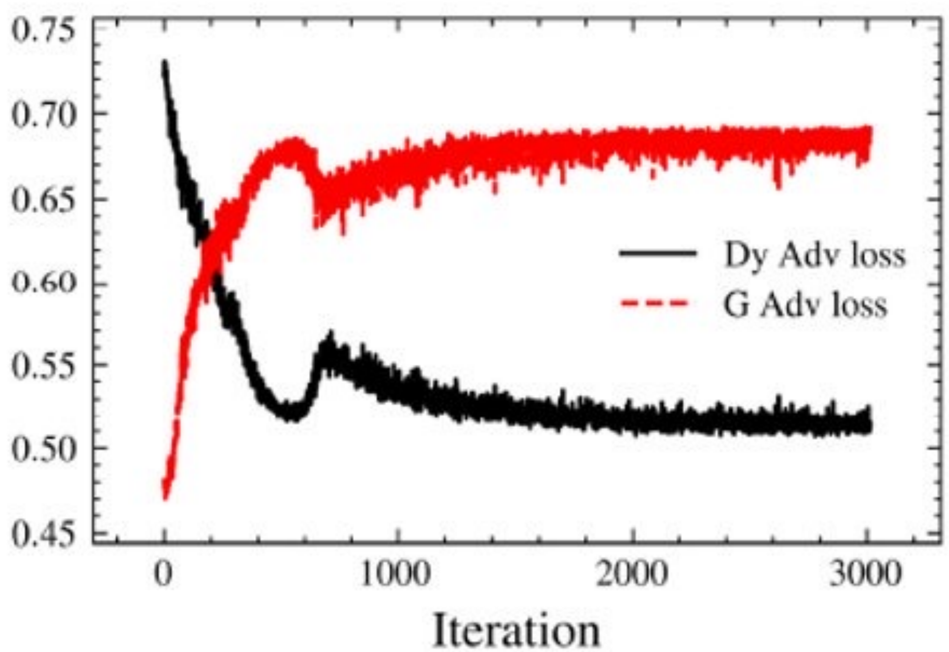
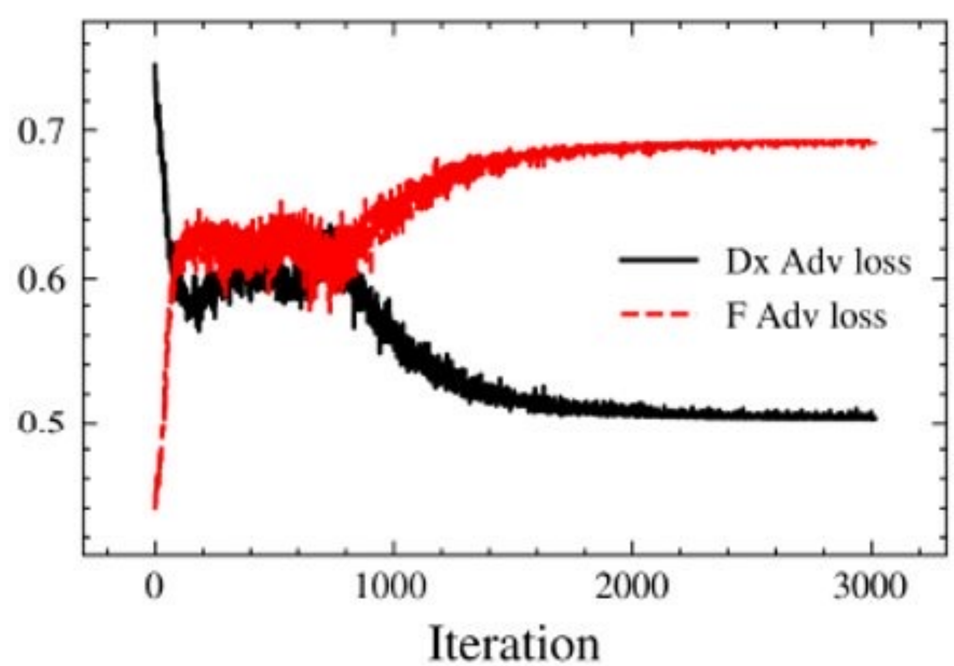
Cycle GAN: Framework





Grid State Generator Neural Network - G	
Nodes	Input: 759 L_1:512, L_2:1024, L_3:2048, L_4:1024, L_5:512 Output: 235
Activation	relu, relu, relu, relu, relu, tanh
Grid State Discriminator Neural Network- D_x	
Nodes	Input: 235 L_1:512, L_2:1024, L_3:256, L_4:64 Output: 1
Activation	relu, relu, relu, relu, sigmoid
Grid Measurement Generator Neural Network - F	
Nodes	Input: 235 L_1:512, L_2:1024, L_3:2048, L_4:1024, L_5:512 Output: 759
Activation	relu, relu, relu, relu, relu, tanh
Grid Measurement Discriminator Neural Network- D_y	
Nodes	Input: 759 L_1:512, L_2:1024, L_3:256, L_4:64 Output: 1
Activation	relu, relu, relu, relu, sigmoid

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Proposed Algorithm

- **Detection**:
  - Residual-based: If $|y_i - F(G(y))_i| \geq \alpha$,i^{th} component is labelled as attacked
- **Reconstruction**:

  Problem formulation: $\mathcal{P}_{err}: \min_{y} ||y - F(G(y))||_2^2$

  Gradient computation: $\frac{\partial f}{\partial y} = -2 \cdot (y - F(G(y))(1 - \frac{\partial F(G(y))}{\partial G(y)} \frac{\partial G(y)}{\partial y})$

  Iterative update rule: $y_{t+1} = y_t - 2\beta\, sgn(y_t - m_t)(y_t - m_t) \frac{\partial f(y_t)}{\partial y}$

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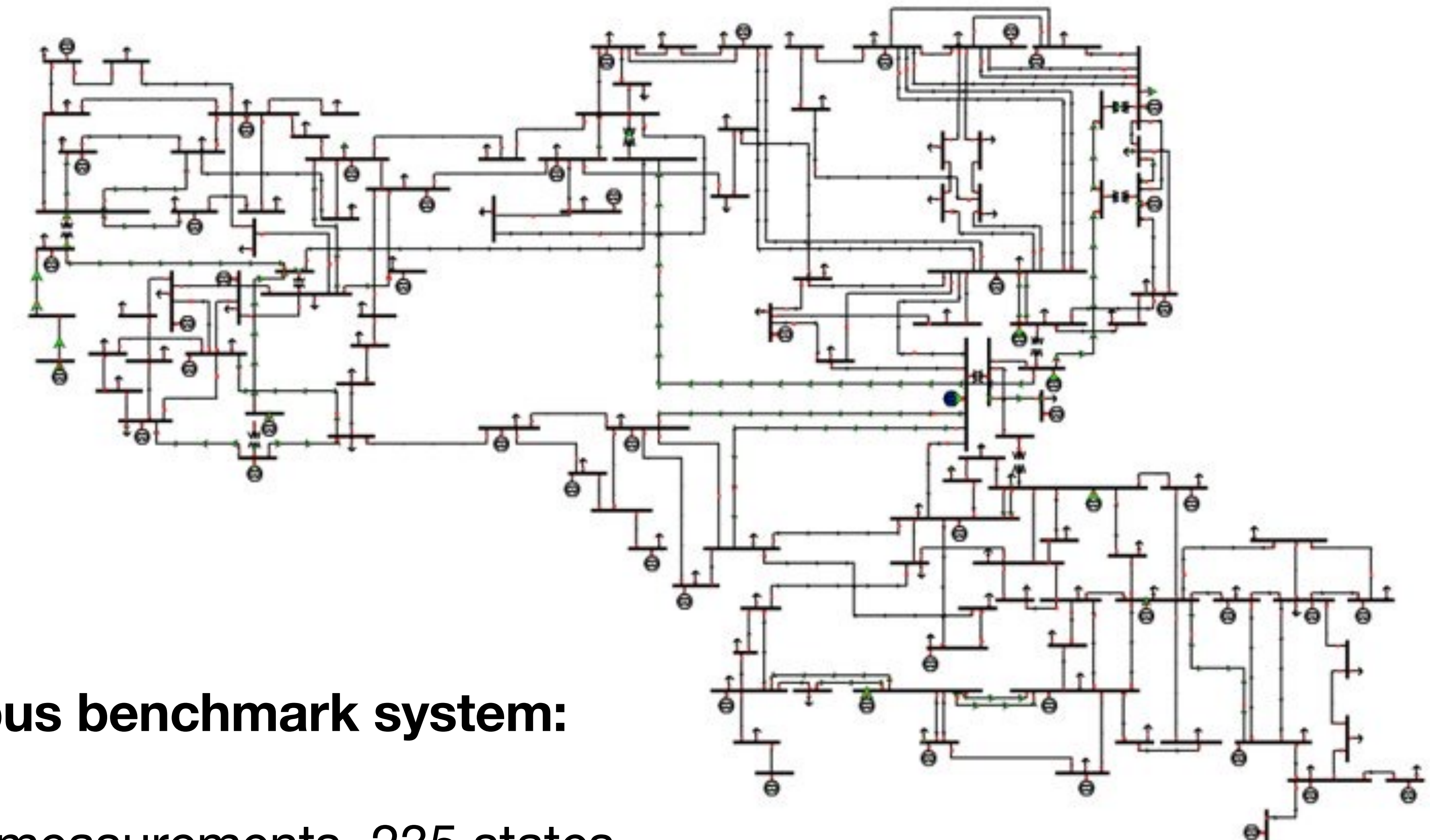
Results



- **IEEE 118-bus benchmark system:**
  - 759 grid measurements, 235 states
- **Attack simulation:**
  - Randomly selected columns , ±10% perturbation

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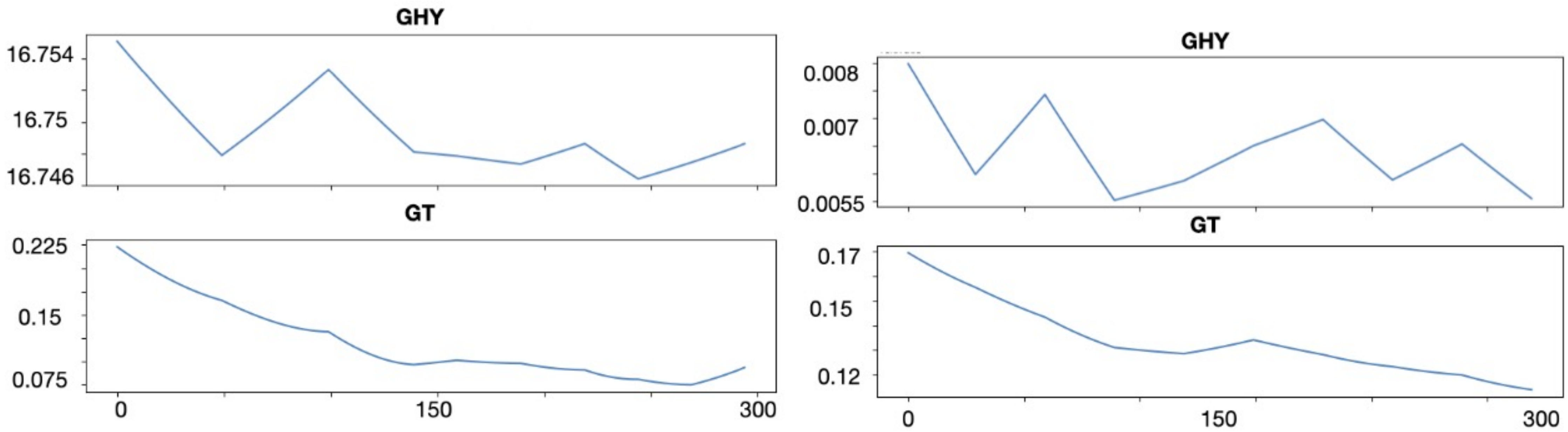
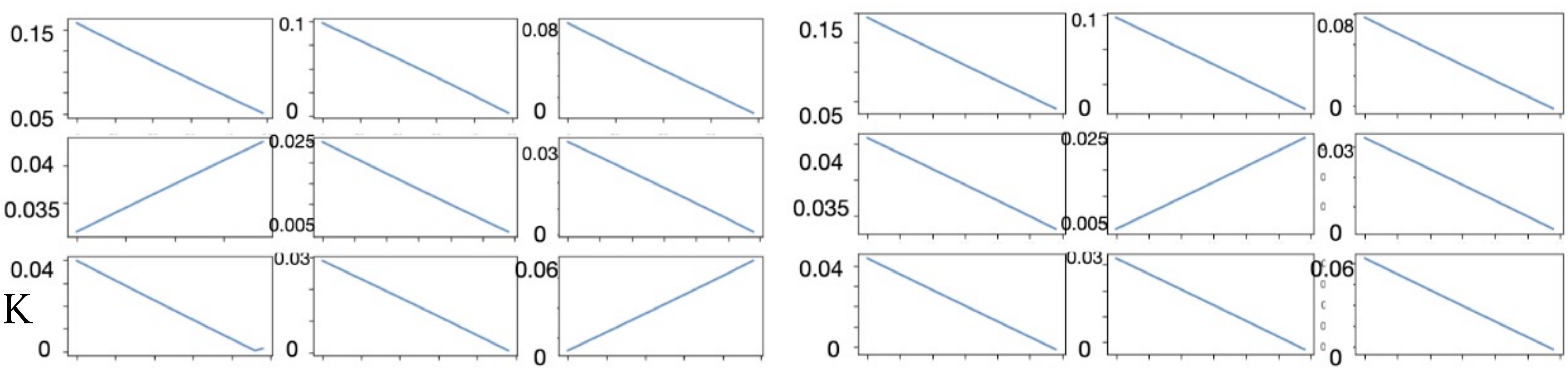
Results



G(H(y)) and GT error for two different cases.



Component-wise ground truth error.

Conclusion

- **Novel reconstruction method:**
  - No need for underlying knowledge of grid topology and parameters
  - Inferencing is computationally inexpensive after training Cycle GAN
  - Effective for high rates of perturbation
- **Future work:**
  - Iterative revisions reach 0 most of the time but is not stopped at these points
  - Need to identify an effective stopping criteria

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References

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