# Modeling Dynamic Response of Inverter-Based Resources Using Waveform Measurements

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Acknowledgement: Fatemeh Ahmadi (Ph.D. Student)

**Grid Disturbances** 



Inverter-Based Resource (IBR)



<sup>1</sup> P. Khaledian and H. Mohsenian-Rad, "Automated Event Region Identification and its Data-Driven Applications in Behind-the-Meter Solar Farms Based on Micro-PMU Measurements," in *IEEE Trans. on Smart Grid*, May 2021.



<sup>2</sup> F. Ahmadi and H. Mohsenian-Rad, "Data-Driven Models for Sub-Cycle Dynamic Response of Inverter-Based Resources Using WMU Measurements," Submitted to *an IEEE Journal* (Under Review), January 2023.



<sup>2</sup> F. Ahmadi and H. Mohsenian-Rad, "Data-Driven Models for Sub-Cycle Dynamic Response of Inverter-Based Resources Using WMU Measurements," Submitted to *an IEEE Journal* (Under Review), January 2023.

• **Q**: How do we know that this is a "Response" and not the "Cause"?



IBR 1 / WMU 1

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Different Feeders, Similar Inverters, Different Sizes

# Modeling Dynamic Response of IBRs

• **Q**: How can we **model** the IBR's sub-cycle dynamic response?





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# **Differential Waveform Dynamics**

• We use Differential Waveform to obtain the model:





- Field Data Set:
  - PV Unit: 480 V / 100 kW
  - Six Months of WMU Data



63 Disturbances (Differential Voltage and Current Waveforms)



• Option 1: Single Model

$$\Delta v(t) \longrightarrow f(\cdot) \longrightarrow \Delta i(t)$$

Train  $f(\cdot)$  to reach the best match between all 42 pairs of training data:

$$e_{1}(t) = \Delta i_{1}(t) - f(\Delta v_{1}(t))$$

$$e_{1}(t) = \Delta i_{1}(t) - f(\Delta v_{1}(t))$$

$$\vdots$$

$$e_{42}(t) = \Delta i_{42}(t) - f(\Delta v_{42}(t))$$
(Same Model)

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(Same Model)
Poor Performance!

• Option 2: Multiple Models

$$\Delta v_{1}(t) \rightarrow f_{1}(\cdot) \rightarrow \Delta i_{1}(t)$$

$$\Delta v_{2}(t) \rightarrow f_{2}(\cdot) \rightarrow \Delta i_{2}(t)$$

$$\vdots$$

$$\Delta v_{42}(t) \rightarrow f_{42}(\cdot) \rightarrow \Delta i_{42}(t)$$

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• Summary of Options<sup>2</sup>:



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# Step 1: Modal Analysis

- Consider one pair of training data:  $\Delta v(t)$  and  $\Delta i(t)$ .
- Apply modal analysis (e.g., Prony Method) with *M* modes to obtain:

$$\Delta v(t) = \sum_{m=1}^{M} A_m e^{\sigma_m t} \cos(\omega_m t + \phi_m),$$

$$\Delta i(t) = \sum_{m=1}^{M} B_m e^{\sigma_m t} \cos(\omega_m t + \psi_m),$$

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• At dynamic each mode m, we can define the equivalent admittance of the IBR at that particular mode  $z_m = \sigma_m + j\omega_m$  as the following complex number:

$$\mathbf{H}_m = \frac{B_m \angle \psi_m}{A_m \angle \phi_m} = \frac{B_m}{A_m} \angle (\psi_m - \phi_m) \quad \text{at} \quad \sigma_m + j\omega_m.$$

# Step 2: Library Construction

• Now consider all the K = 42 pairs of training data.

• We can construct a *library* of  $K \times M$  dynamic models:

$$\mathbf{H}_m^k$$
 at  $z_m^k = \sigma_m^k + j\omega_m^k$ ,  $k = 1, \dots, K$ ,  
 $m = 1, \dots, M$ .

• Each model corresponds to **one** dynamic mode that is derived from **one** disturbance; thus adding up to  $K \times M$  models using modal analysis.

# Step 3: Model Selection

• Let  $\Delta v_{\text{test}}(t)$  and  $\Delta i_{\text{test}}(t)$  denote the differential voltage and the differential current waveform for a given test disturbance.

• Apply modal analysis to the input test signal:

$$\Delta v_{\text{test}}(t) \longrightarrow$$
 Dynamic Modes:  $z_{n,\text{test}} = \sigma_{n,\text{test}} + j\omega_{n,\text{test}}$ 

• For any such dynamic mode *n*, we obtain (based on input-voltage):

$$\left[k_{n}^{\star}, m_{n}^{\star}\right] = \underset{k,m}{\operatorname{arg\,min}} \left|z_{n, \text{test}} - z_{m}^{k}\right|^{2}.$$

(Minimum Model Distance)

# Step 3: Model Selection (Cont.)

• Accordingly, we obtain *n* models corresponding to the *n* modes:



# Step 4: Dynamic Response Estimation

- Given  $\mathbf{H}_{m_1^{\star}}^{k_1^{\star}}, \mathbf{H}_{m_2^{\star}}^{k_2^{\star}}, \cdots, \mathbf{H}_{m_M^{\star}}^{k_M^{\star}}$  for each test input voltage signal  $\Delta v_{\text{test}}(t)$ .
- We estimate the output signal  $\Delta i_{test}(t)$  as follows:

$$\hat{\Delta i}_{\text{test}}(t) = \sum_{n=1}^{M} C_n e^{\sigma_{n,\text{test}}t} \cos(\omega_{n,\text{test}}t + \varphi_n),$$

where

$$C_n = A_{n,\text{test}} \left| \mathbf{H}_{m_n^{\star}}^{k_n^{\star}} \right|, \quad \varphi_n = \phi_{n,\text{test}} + \angle \mathbf{H}_{m_n^{\star}}^{k_n^{\star}}.$$

# Some Experimental Results

- Results best on 21 Test Disturbances (Out-of-Sample Tests)
- Baseline method: Single Model Approach



• Additional modes improve performance (bigger library).

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• Impact of **Modal Distance** (of Individual Test Samples):



• Shorter modal distance (from library) leads to better output estimation.

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# Some Potential Use Cases

• 1) Dynamic Analysis of Individual IBRs (Diagnosis, Trip Prediction, etc.)

• 2) Comparing Dynamic Response of IBRs (Synchro-Waveforms)

- 3) Aggregate Dynamic Response
- 4) Potential Ripple Effects
- 5) Other (To be Explored)



• WMU-Based Dynamic Load Modeling (Will be Published Soon):

F. Ahmadi and H. Mohsenian-Rad, "Data-Driven Models for Sub-Cycle Dynamic Response of Inverter-Based Resources Using WMU Measurements," *Submitted to an IEEE Journal* (Under Review), January 2023.

• WMUs and Synchro-Waveforms:

[1] M. Izadi and H. Mohsenian-Rad, "Characterizing synchronized Lissajous curves to scrutinize power distribution synchro-waveform measurements," in *IEEE Trans. on Power Systems*, vol. 36, no. 5, p. 4880, Sept 2021.

[2] M. Izadi and H. Mohsenian-Rad, "Synchronized Lissajous-based method to detect & classify events in synchro-waveform measurements in power distribution networks," in *IEEE Trans. on Smart Grid*, vol. 13, May 2022.

[3] M. Izadi and H. Mohsenian-Rad, "synchronous waveform measurements to locate transient events and incipient faults in power distribution networks," in *IEEE Trans. on Smart Grid*, vol. 12, no. 5, pp. 4295, Sept 2021.

#### Chapter 4



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#### **Thank You!**

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