Using Probing Input Signals for Enhanced Power Grid Monitoring and Control

SEGIP CT Identification Study Day
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ALSETLab

Outline

- Acknowledgements
- Background
- System Identification and Optimal Probing Design
  - System Identification and Experiment Design
  - Prediction Error Method (PEM)
  - Optimization Problem using PEM → Optimal Probing Signal Design
- Real-Time Prototyping
  - Modeling and simulation needs and how Modelica and the FMI can help
  - OpenIPSL: a power systems modeling library in Modelica
  - Real-Time Prototyping using the FMI and a dSPACE SCALEXIO RTS
- Conclusions
- References

Acknowledgements

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  - Ecole Central de Lyon, Ecully, France
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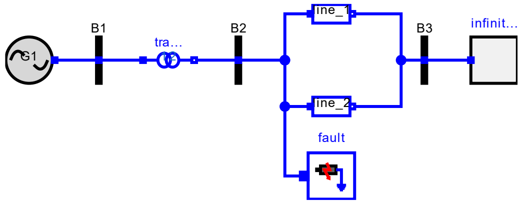
Background – Power system stability

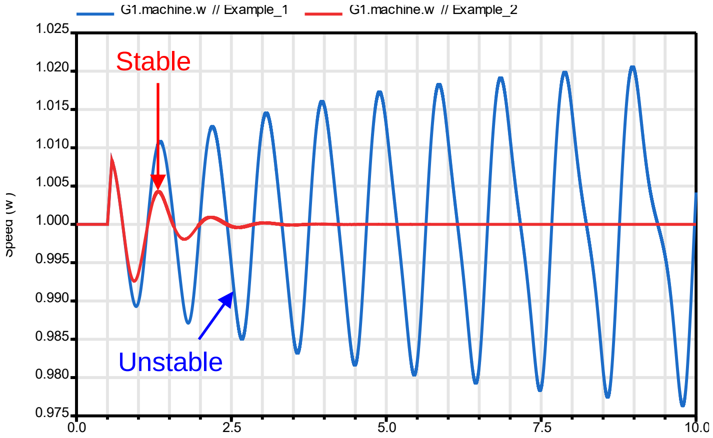
Power systems undergo multiple types of perturbations, e.g., turn on/off consumers, and contingencies, e.g., faults, line trips, etc.

- These produce a disturbance forces.
- The interconnected machines need to develop restoring forces that are equal or greater than the disturbance forces.
- If the synchronous machines stay in synchronism and overcome the disturbing forces, we say that the system is stable.
- If not, the systems is unstable.

- To keep a system stable, multiple apparatus and their control loops need to function properly, which may not be the case as system conditions change.
- We want to be able to monitor what is the "degree" of stability for these dynamics as system conditions change,
  - But to monitor something, we need to know how to ***quantitatively*** characterize it!

- **Example:**
  - Single Machine Infinite-Bus Model from the OpenIPSL Modelica Library under `Examples.Tutorial`, `Example_1 and Example_2`





Background – Characterization of system dynamics

Characterizing electromechanical dynamics:

- The ability of the power system to adjust to different perturbations requires the system to be small-signal stable, e.g., tracking the increase of consumption, moving power plants from one operating point to another.
- We could do a simulation to see if the system can track such changes, i.e., stable or unstable., but it doesn't tell us the degree of stability (how stable or unstable).

Linear Analysis: can provide much more information, such as the modes of instability and margins.

- Let the nonlinear power system mode be defined by

$$\dot{x} = f(x) \rightarrow x(t) = x(0) + \int_0^t f\big(x(t)\big)dt$$

- Defining $y = x - x^*$, in a small neighborhood around the equilibrium, then:

$$y = f(x^*) + \boldsymbol{A}y + O\big(|y^2|\big) \approx \boldsymbol{A}y$$

- where $\boldsymbol{A} = \left.\frac{\partial f}{\partial x}\right|_{x^*}$ is the state matrix.
- The solution of such linear system exists and is of the form:

$$x(t) = e^{\boldsymbol{A}t}x(0)$$

Modes: eigenvalues

Letting x be a vector, we can decompose the state equation into a system of n decoupled 1st order systems.

- This boils down to finding the solution to

$$\det(\boldsymbol{A} - \boldsymbol{\lambda I})$$

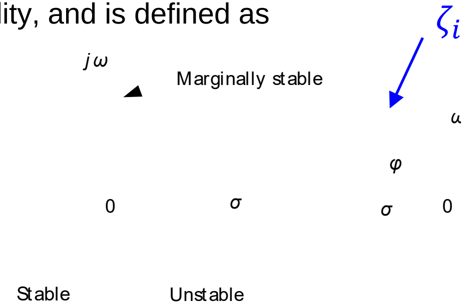
- where $\boldsymbol{\lambda}$ is a vector containing the eigenvalues of $\boldsymbol{A}$, and where each eigenvalue is given by

$$\lambda_i = \alpha_i + j2\pi f_i$$

- Which means that every λ_i, corresponds to a mode with a frequency f_i

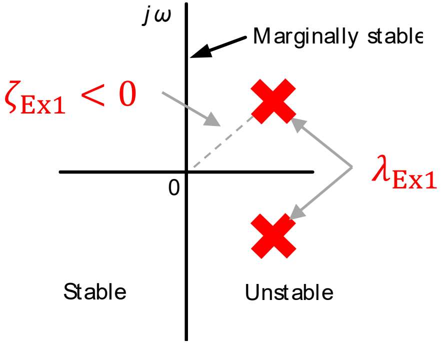
Damping: is the metric ***for each mode*** that will allow us to determine the degree of stability, and is defined as

$$\zeta_i = -\frac{\alpha_i}{\sqrt{\alpha_i^2 + (2\pi f_i)^2}}$$



Example: SMIB of OpenIPSL under `Examples.Tutorial`, `Example_1` and `Example_2`

- Example 1:



	xNames =
1	G1.avr.vm
2	G1.avr.vr
3	G1.avr.vf1
4	G1.machine.delta
5	G1.machine.w
6	G1.machine.e1q
7	G1.machine.e1d
8	G1.machine.e2q
9	G1.machine.e2d

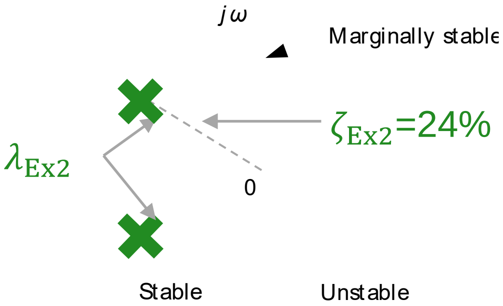
A =

	1	2	3	4	5	6	7	8	9
1	-66.6667	0	0	-9.194	0	0	0	33.3636	29.2554
2	0	-1	0	0	0	0	0	0	0
3	-2e+06	10000	-10000	0	0	0	0	0	0
4	0	0	0	0	376.991	0	0	0	0
5	0	0	0	-0.15935	0	0	0	-0.17302	0.0600076
6	0	0	0.124969	-0.225787	0	-0.125	0	-0.26689	-0.00110411
7	0	0	0	0.46108	0	0	-1	0.00633642	-1.48943
8	0	0	0.00833333	-2.97283	0	33.3333	0	-36.8474	-0.0145373
9	0	0	0	2.62156	0	0	14.2857	0.036027	-22.7542

eigenvalue	freq. [Hz]	damping	characteristics
3.5175e-01 ± 8.0657e+00j	1.2849	-0.0436	not stable, not stabilizable, not detectable
-1.5082e+01 ± 1.3526e+01j	3.2242	0.7445	stable, not controllable, not observable

λ_{Ex1}

- Example 2:



	xNames =
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4	G1.machine.delta
5	G1.machine.w
6	G1.machine.e1q
7	G1.machine.e1d
8	G1.machine.e2q
9	G1.machine.e2d
10	G1.pss.imLeadLag.TF.x_scaled[1]
11	G1.pss.imLeadLag1.TF.x_scaled[1]
12	G1.pss.derivativeLag.TF.x_scaled[1]

A =

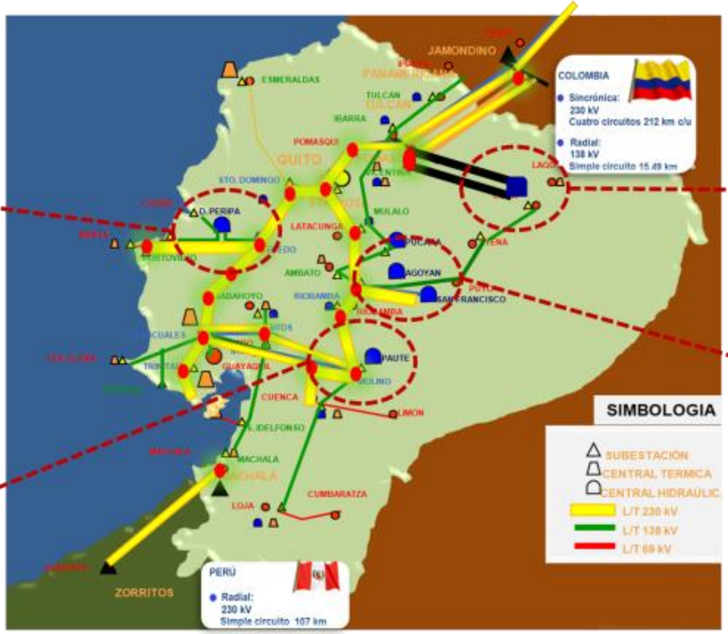
	1	2	3	4	5	6	7	8	9	10	11	12
1	-66.6667	0	0	-9.194	0	0	0	33.3636	29.2554	0	0	0
2	0	-1	0	0	0	0	0	0	0	0	0	0
3	-2e+06	10000	-10000	0	8.86667e+07	0	0	0	0	-7.33333e+06	0	-8.86667e+07
4	0	0	0	0	376.991	0	0	0	0	0	0	0
5	0	0	0	-0.15935	0	0	0	-0.17302	0.0600076	0	0	0
6	0	0	0.124969	-0.225787	0	-0.125	0	-0.26689	-0.00110411	0	0	0
7	0	0	0	0.46108	0	0	-1	0.00633642	-1.48943	0	0	0
8	0	0	0.00833333	-2.97283	0	33.3333	0	-36.8474	-0.0145373	0	0	0
9	0	0	0	2.62156	0	0	14.2857	0.036027	-22.7542	0	0	0
10	0	0	0	0	287.879	0	0	0	0	-30.303	0	-287.879
11	0	0	0	0	0.0443333	0	0	0	0	-0.00366667	-0.001	-0.0443333
12	0	0	0	0	0.70922	0	0	0	0	0	0	-0.70922

eigenvalue	freq. [Hz]	damping
-1.8002e+00 ± 7.2294e+00j	1.1857	0.2416
-9.8067e+00 ± 1.7110e+01j	3.1387	0.4973

λ_{Ex2}

Background - Ecuador's Grid Dynamics

- In real-world networks, there are multiple modes with different type of interactions.
  - Intra-plant: interactions between individual generator units within the same plant.
  - Local: a plant against another plant or groups of plants.
  - Inter-area: groups of plants against other group of plants.



1.0 – 1.8 Hz
Local Mode

0.7 – 1.2 Hz
Local Mode

0.34 – 0.45 Hz
Inter-area Mode

0.8 – 1.1 Hz
Local Mode

0.34 – 0.45 Hz
Inter-area Mode

Torre, Aharon & Cepeda, Jaime & Herrera, J.. (2013). Implementación de un sistema de monitoreo de área extendida WAMS en el Sistema Nacional Interconectado del Ecuador SNI. Ingenius. 10.17163/ings.n10.2013.04.

Background – Dynamics monitoring tech.

Phasor Measurement Units (PMU)

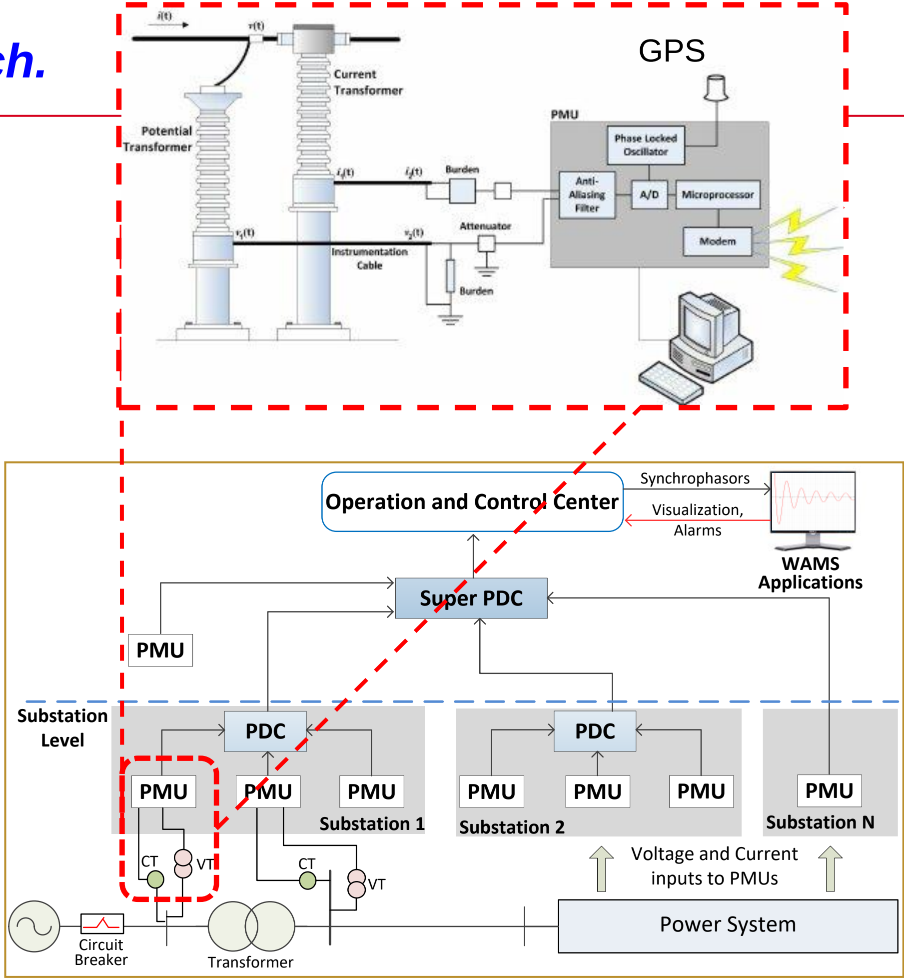
- An Intelligent Electronic Device (IED) that can provide an estimated/measured value of a phasor (magnitude and angle).
- Data is time-synchronized using GPS disciplining.
- Data is reported (streamed) at 30/60/120 samples/sec using TCP or UDP over IP.
- IEEE C37.118.2 protocol for data transport.

WAMS – Wide-Area Monitoring Systems

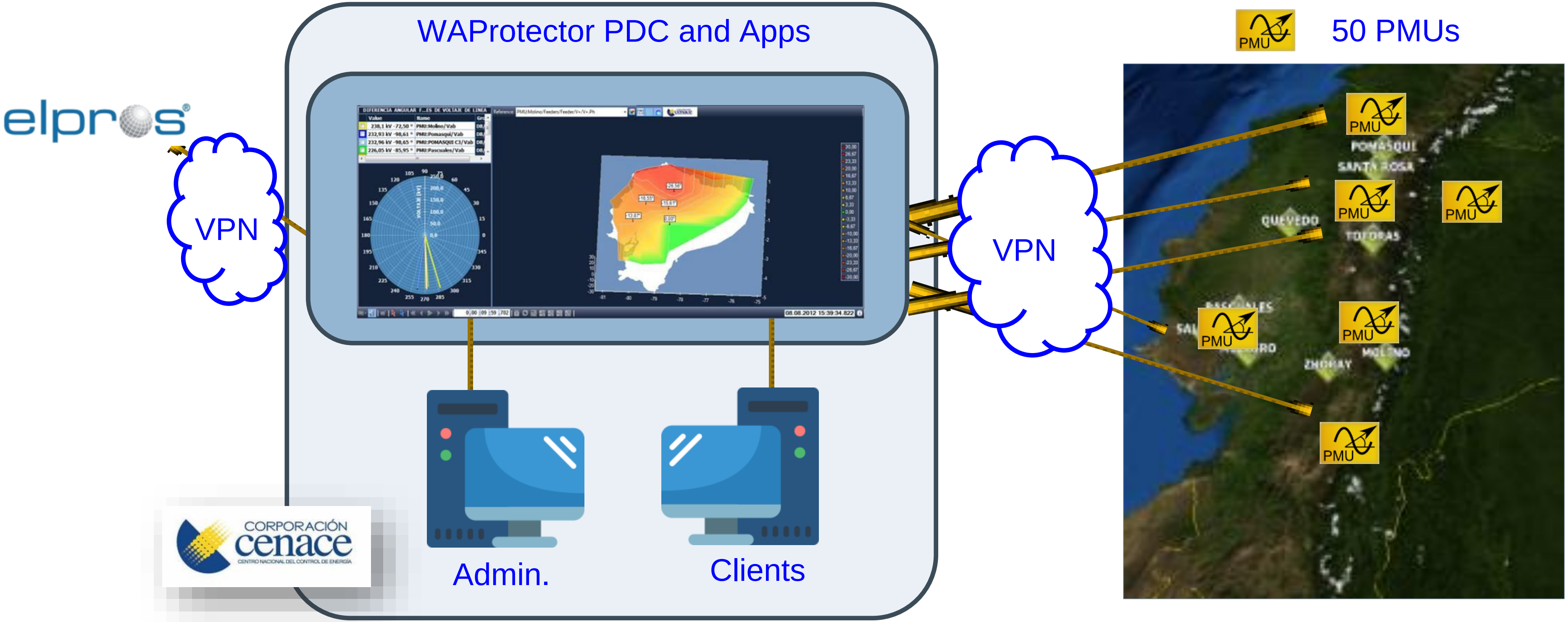
- A system that networks multiple PMUs
- PDC time-aligns and aggregates them, providing a single output stream for applications or a Super PDC

WAMS Applications:

- Monitoring – provide fast updates (near real-time) for operator situational awareness.
- **Oscillation Monitoring Software** helps monitor grid dynamics (multiple modes frequency and damping)



Background - Ecuador's WAMS System

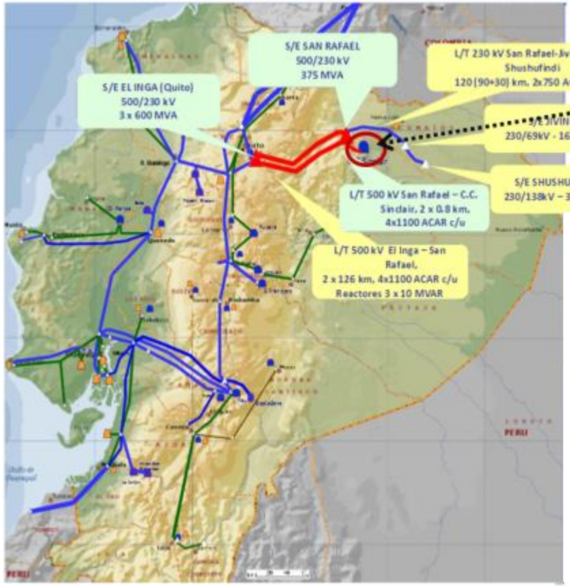


* Jaime Cristobal Cepeda, "Testbed for Power System Stabilizer Tuning using Synchrophasor measurements and eMEGAsim," RT20 Virtual Edition, June 18-19, 2020.

Background: Need for dynamic monitoring

ALSET lab

- Coca Codo Sinclair (CCS): 1500 MW Hydroelectric Power Plant
  - Commissioning testing measurements of the Sta. Rosa – Sto. Doming 230 kV transmission line
  - Negative damping of -1.9% at 0.752 Hz
  - Solved by Power System Stabilizer re-design/tuning*



$\zeta_{Ex1} < 0$

* Jaime Cristobal Cepeda, "Testbed for Power System Stabilizer Tuning using Synchrophasor measurements and eMEGAsim," RT20 Virtual Edition, June 18-19, 2020.

Background – Why measurement-based models?

- **Power system *computer simulation models*** allow to perform multiple analysis, and when validated, can characterize the grid's dynamics over a "large frequency bandwidth"*, capture nonlinearities, etc.

- However, they ***are difficult to maintain*** with the required accuracy and precision ***and use***, specially for ***near/real-time grid dynamics monitoring and control*** purposes.

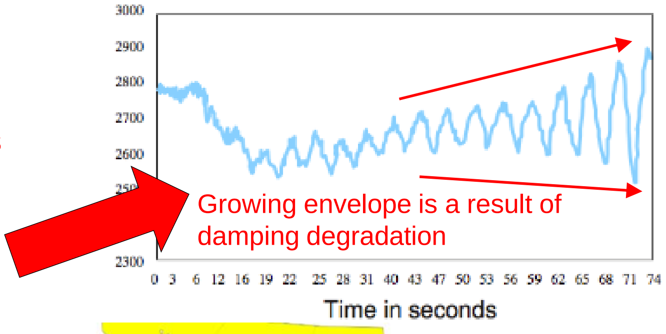
- Alternatively, ***other type of models*** (e.g., transfer function representations):
  - can be ***identified from measurement data***,
  - **under "normal" operating conditions** using "ambient data",
  - *during large disturbances* (e.g., loss of an important line) using "transient data", and
  - ***under stagged tests (experiments)*** by intentionally "probing" the system by injecting small signals into available control inputs.

- While these models are limited by the measurements available (bandwidth):
  - they ***can give a useful representation*** certain system characteristics (e.g., damping of critical grid dynamics or the spectrum over a frequency range), ***for monitoring and control design***
  - **by specifying constraints on** their required accuracy and precision on the **estimated parameters** (variance requirements).

Background – What are we trying to characterize?

Models identified from measurement data can help characterize:

- What are the system dynamics being excited?
- Are the they stable or unstable?
- How stable is the system w.r.t. the dynamics being excited? Or, how close is the system to lose stability?
- ***Example:*** Lightly damped oscillations lead to a system black-out and break-up of interconnection.

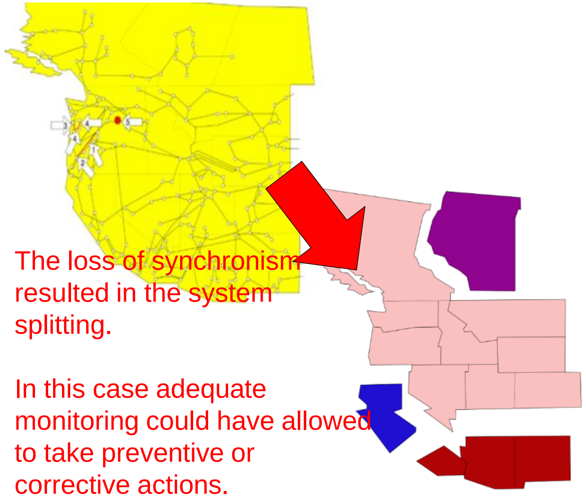


To identify a model that captures this behavior, let's assume that:

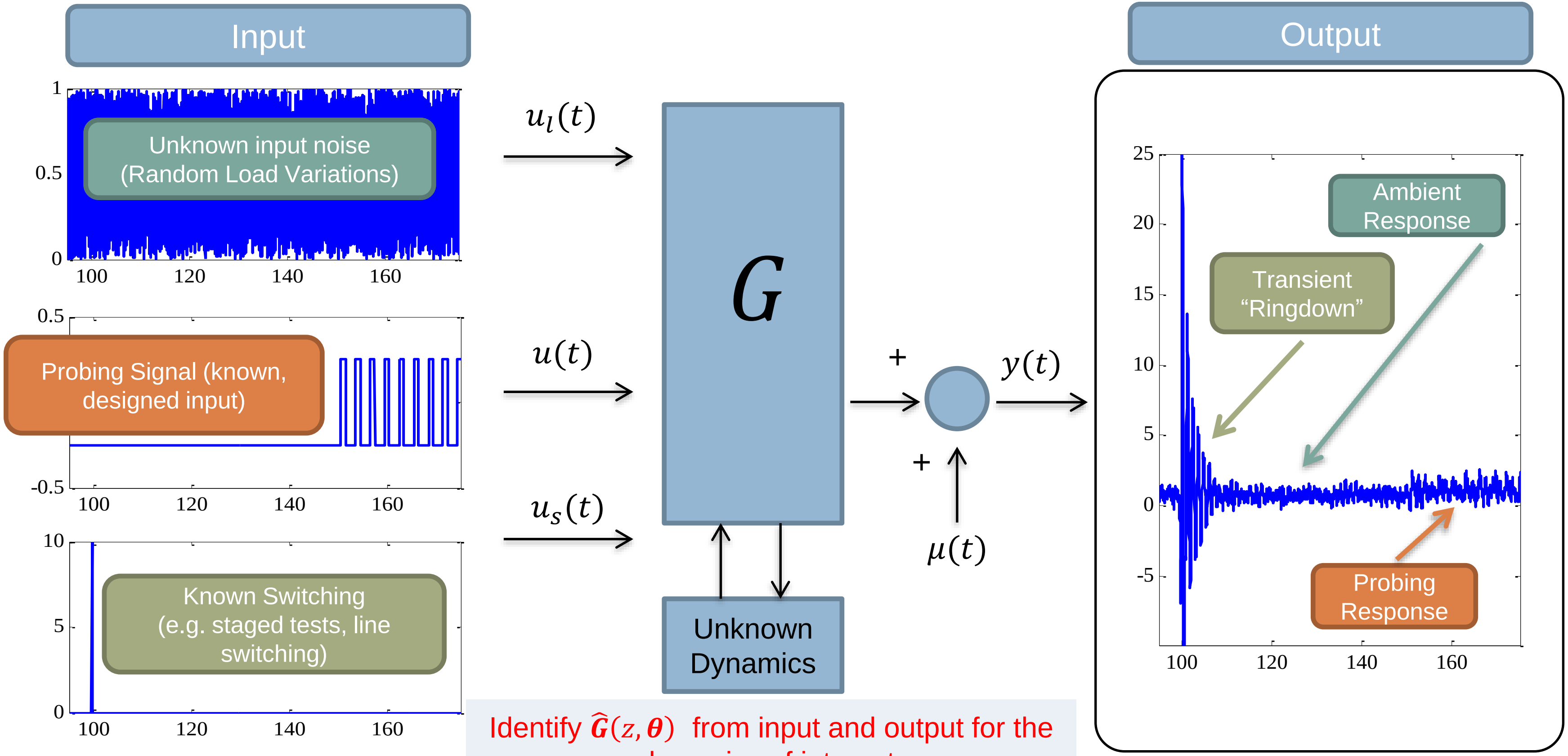
- The system operates in near equilibrium (less "wiggles" visible), i.e., so called steady state, and is excited only by small changes
- Then, we can **approximate** the system to a linear model:

$$\hat{\boldsymbol{G}}(z,\boldsymbol{\theta}) = \frac{z^{-n_k}\boldsymbol{B}(z,\boldsymbol{\theta})}{\boldsymbol{A}(z,\boldsymbol{\theta})}$$

- where the poles of $\boldsymbol{A}(z,\boldsymbol{\theta})$ contain the critical information about the system's response.
- We can transform this model from discrete-time to a continuous time representation with, e.g., Tustin's approx., resulting in $\hat{\boldsymbol{G}}(s,\boldsymbol{\theta})$.
- From where we can extract the damping and frequency of $\boldsymbol{i}$-th "mode", $\hat{\boldsymbol{\zeta}}_{\boldsymbol{i}}$ and $\hat{\boldsymbol{\omega}}_{\boldsymbol{i}}$.



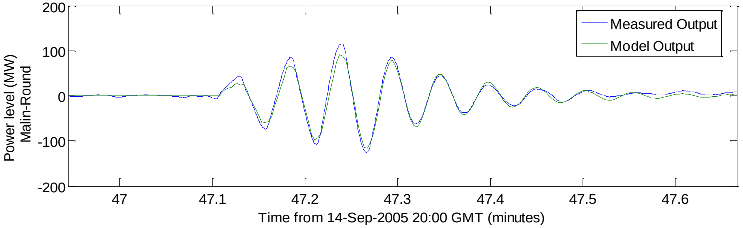
Background – Types of System Response



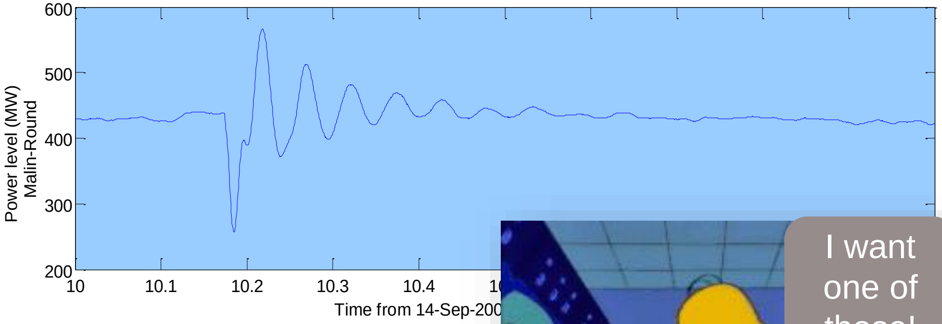
Identify $\widehat{\boldsymbol{G}}(z, \boldsymbol{\theta})$ from input and output for the dynamics of interest.

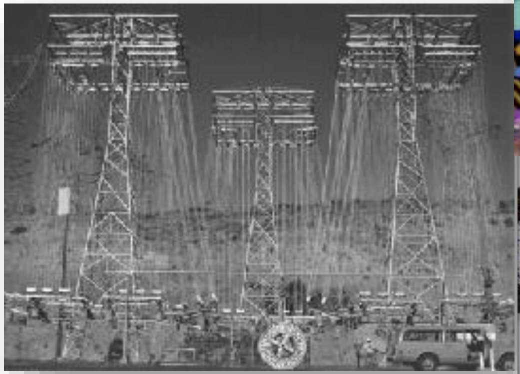
Background – Transient Response

- Experiments at the "system scale" are very rare in high voltage electrical power networks, but they do exist!
- "The Toaster" (Chief Joseph Dynamic Breaker) is one of the few facilities in the world that allows to make a "breaker insertion" capable of producing a large transient in the system.
- One of its uses has been in providing reference values to tune mode meters and model:



0.3 Hz Validation

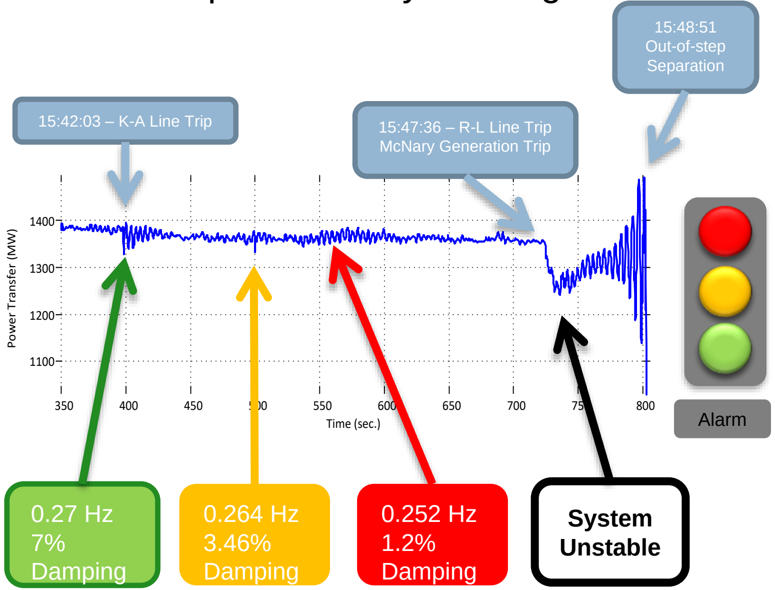


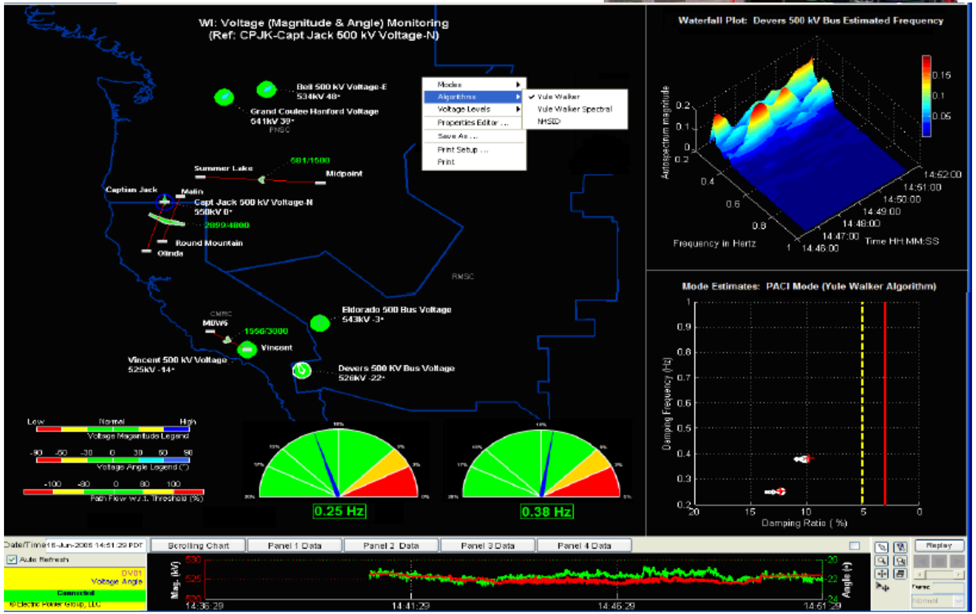


[BPA] "It can consume 1,440 MW - more than the output of Bonneville Dam. It's only capable of staying on for 3 seconds - beyond that, it would destroy itself."

Background – Ambient Response

- ***Monitoring using ambient data:***
  - Use the measurement data to estimate $\hat{G}(z, \theta)$, extract the values of the damping and frequency of i-th "mode", $\hat{\zeta}_i(t)$ and $\hat{\omega}_i(t)$, and set thresholds to the provide early warning indicators.



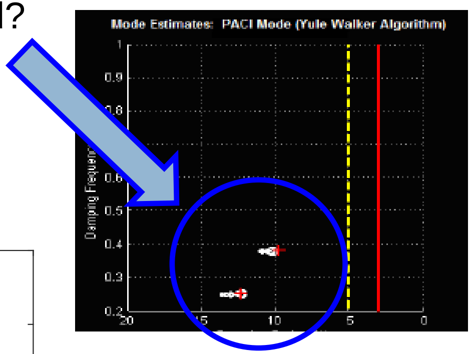


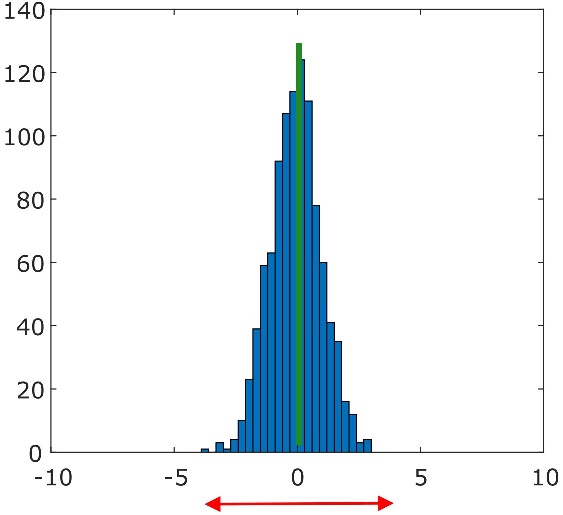
Background – What is a good mode meter estimate?

- How can you tell if your estimated $\boldsymbol{i}$-th "mode", $\hat{\zeta}_i(t)$ and $\hat{\omega}_i(t)$, values are good?
- Illustrative Example:

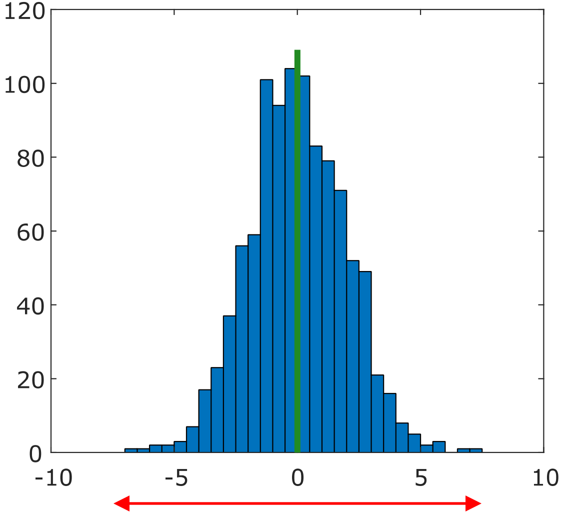
$$\zeta_{\text{true}} = 0.1 \qquad \hat{\zeta} = 0.09$$

  - Is $\hat{\zeta} = 0.09$ a good estimate?
- **It all depends on its mean and variance!**





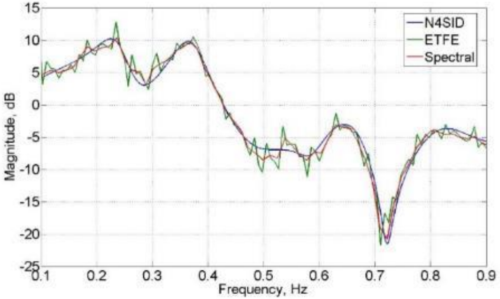
Lower variance, better estimate.



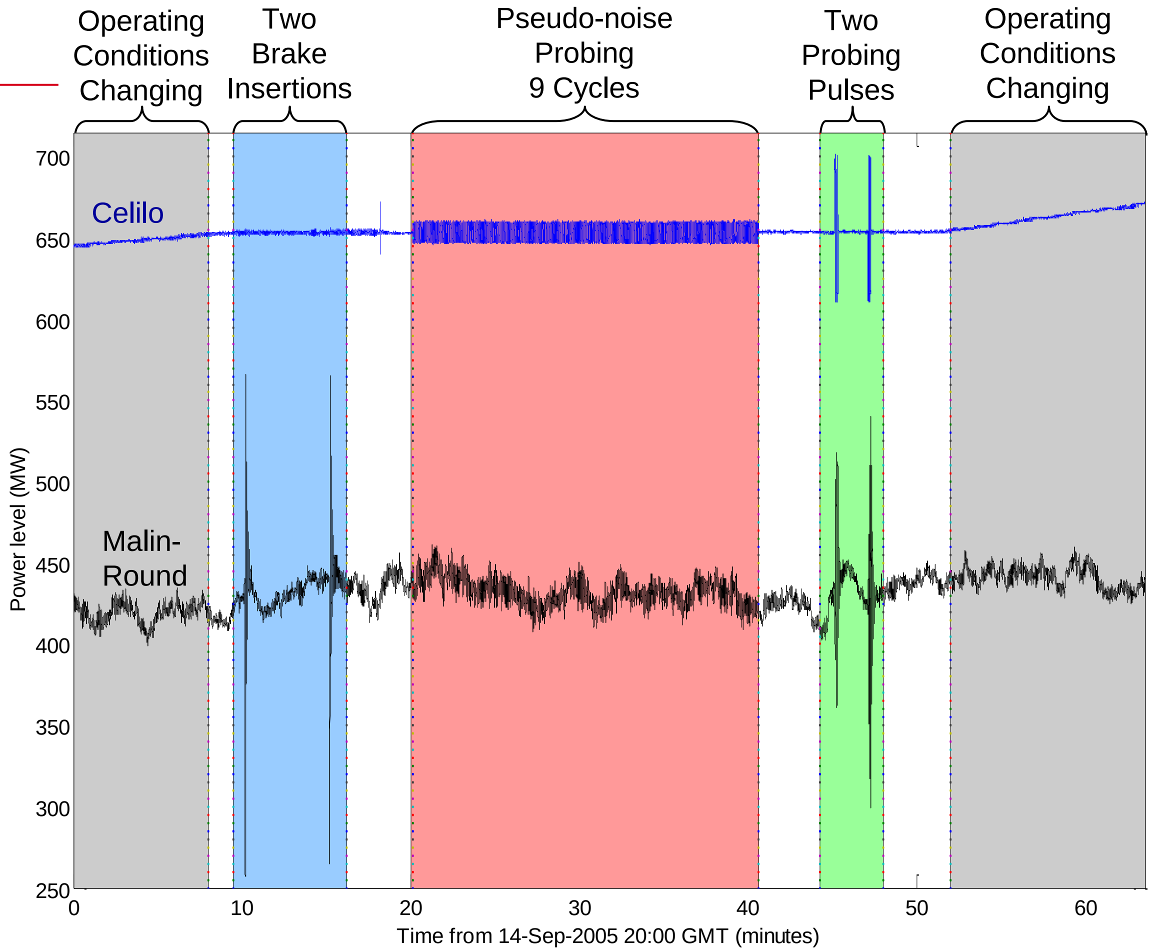
Larger variance, worse estimate.

Background – Probing

- Injecting a small probing signal in the DC Pacific Intertie:

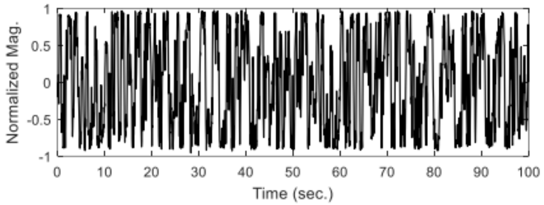


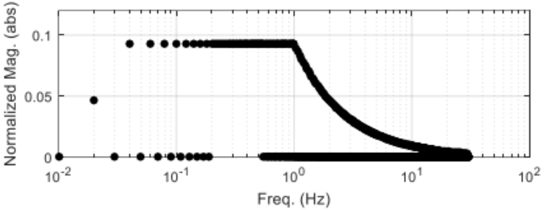
2006 Test

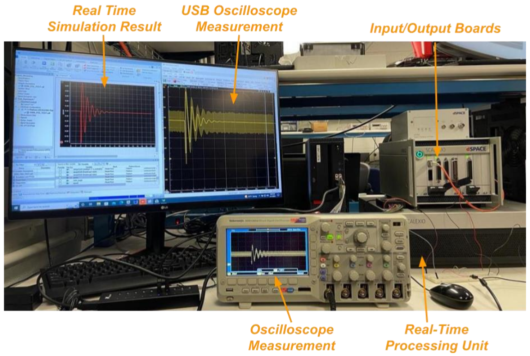


Background – Probing Signals

- State-of-the-art, probing experiments in the WECC
  - Excite the system using the PDCI control input through a +20 MW pseudorandom signal (see 2021 WI Modes Review Report, <u>here</u>)
- Multi-sine probing signal designed to excite a specific frequency range (with a priori knowledge):
  - Max. energy for a given peak-to-peak limit (adjust phase per sinusoid)
  - Most of its content in the 0.1 Hz to 1 Hz range
  - Applied to the PDCI for 10 to 20 minutes
- Research Questions:
  - How to *design signals for systems* with "lesser known" (or unknown) and changing *dynamics*?
  - Can we ***reduce the control effort*** *(by minimizing the <u>input signal's</u> spectral power)* or the ***limit the impact on the system*** *(by minimizing the <u>output signal's</u> spectral power)* while **maintaining *high accuracy and precision*** in the estimated parameters (e.g., mode estimate)?
  - How can we test the designed signals before field trials?







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  - Modeling and simulation needs and how Modelica and the FMI can help
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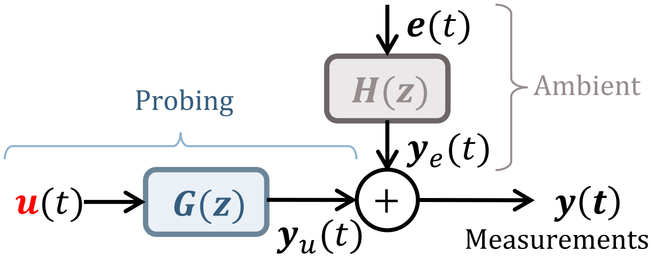
System Identification and Experiment Design

Consider the power system under both ambient load variations and probing input signals:

- *Known:*
  - $\boldsymbol{y}(t)$, the measured system response and
  - $\boldsymbol{u}(t)$, the input signal (deterministic or designed)
- *Unknown:*
  - $\boldsymbol{e}(t)$, disturbance input, random load variations (stochastic)
  - $\boldsymbol{G}(z)$ is the *actual* system between $\boldsymbol{y}_u(t)$ and $\boldsymbol{u}(t)$
  - $\boldsymbol{H}(z)$ is the *actual* system between $\boldsymbol{y}_e(t)$ and $\boldsymbol{e}(t)$

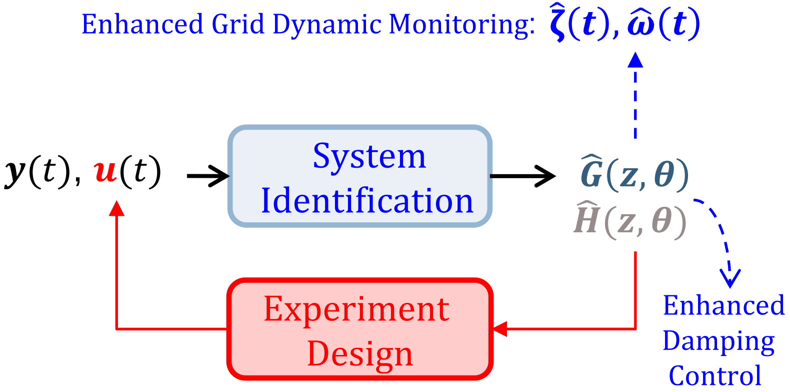


System Identification:

- Obtain *estimated* $\widehat{\boldsymbol{G}}(z,\boldsymbol{\theta})$ and $\widehat{\boldsymbol{H}}(z,\boldsymbol{\theta})$, *a model* (i.e., DT TFs) for a ***pre-scribed*** $\boldsymbol{u}(t)$ where $\boldsymbol{\theta}$ is an unknown parameter vector, $\boldsymbol{\theta} = [\boldsymbol{\theta}_1 \quad \boldsymbol{\theta}_2 \quad \ldots. \quad \boldsymbol{\theta}_N]$ to be estimated
- Use the estimated models to extract $\hat{\boldsymbol{\zeta}}(\boldsymbol{t})$ and $\hat{\boldsymbol{\omega}}(\boldsymbol{t})$ the modes frequency and damping used for monitoring

Experiment Design:

- **Design** $\boldsymbol{u}(t)$ ***with constraints on the accuracy and precision*** of $\hat{\boldsymbol{\zeta}}(\boldsymbol{t})$ and $\hat{\boldsymbol{\omega}}(\boldsymbol{t})$ (enhanced monitoring) or $\widehat{\boldsymbol{G}}(\boldsymbol{z},\boldsymbol{\theta})$ for (enhanced) control purposes



Sys. Identification: Prediction Error Method

In this method we aim to reduce the difference between:

- the measured true system response $\boldsymbol{S} = \{\boldsymbol{G}(z) \quad \boldsymbol{H}(z)\}$, $\boldsymbol{y}(t)$ and
- the prediction $\hat{\boldsymbol{y}}(t)$ estimated from the model $\mathcal{M} = \left\{\widehat{\boldsymbol{G}}(z,\boldsymbol{\theta}) \ \widehat{\boldsymbol{H}}(z,\boldsymbol{\theta}) \ \ \forall\ \boldsymbol{\theta}\epsilon R^2\right\}$, by finding parameter vector $\boldsymbol{\theta_O}$

$$\boldsymbol{\theta_O} = arg\min_{\boldsymbol{\theta}} \frac{1}{N}\sum_{t=1}^{N} \boldsymbol{\varepsilon}^2(t,\boldsymbol{\theta})$$

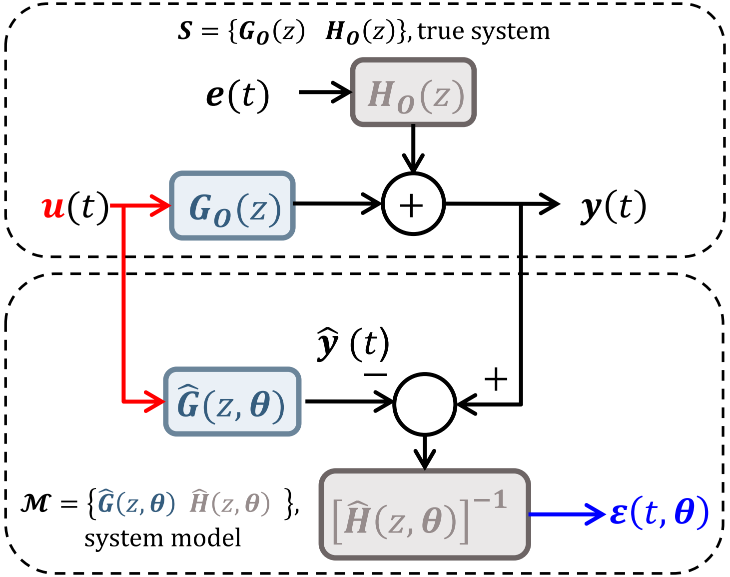
$$\text{subject to } \boldsymbol{\varepsilon}(t,\boldsymbol{\theta}) = \left[\widehat{\boldsymbol{H}}(z,\boldsymbol{\theta})\right]^{-1}\left(\boldsymbol{y}(t) - \widehat{\boldsymbol{G}}(z,\boldsymbol{\theta})\boldsymbol{u}(t)\right)$$

where N is the number of data points in $\boldsymbol{y}(t)$, and **we make N bounded.**

- **The larger the N the better precision**, however, we aim to estimate $\hat{\boldsymbol{\zeta}}(\boldsymbol{t})$ and $\hat{\boldsymbol{\omega}}(\boldsymbol{t})$ every few minutes, e.g., 5-20 min.
- Note that if:

  $$\widehat{\boldsymbol{H}}(z,\boldsymbol{\theta}) = \boldsymbol{H}(z) \text{ and } \widehat{\boldsymbol{G}}(z,\boldsymbol{\theta}) = \boldsymbol{G}(z,\boldsymbol{\theta}) \rightarrow \boldsymbol{\varepsilon}(t,\boldsymbol{\theta}) = \boldsymbol{e}(t)$$

  where $\boldsymbol{e}(t)$ is a *white noise signal*
- In this work, we assume that the system random load variations are independent, and without making any assumptions on their probability distribution functions.



The Prediction Error Method then can be stated as:

Find (an estimate of) the unknown parameter vector $\boldsymbol{\theta} = \boldsymbol{\theta_O}$ that minimizes the power $\boldsymbol{\varepsilon}(t,\boldsymbol{\theta})$ of using a set of N input and output data $\boldsymbol{Z}^N = \{\boldsymbol{u}(t),\ y(t) | t = 1 \ldots N\}$ obtained from the true system $\boldsymbol{y}(t) = G_O\boldsymbol{u}(t) + H_O\boldsymbol{e}(\boldsymbol{t})$

ARMAX Model Parametrization in $\hat{\zeta}_i(t)$ and $\hat{\omega}_i(t)$

Different types of structures can be chosen for the model $\mathcal{M} = \left\{\left(\hat{\boldsymbol{G}}(z,\boldsymbol{\theta}), \hat{\boldsymbol{H}}(z,\boldsymbol{\theta})\right), \boldsymbol{\theta} \in R^{n_\theta}\right\}$, we choose the ARMAX:

$$\hat{\boldsymbol{G}}(z,\boldsymbol{\theta}) = \frac{z^{-n_k}\boldsymbol{B}(z,\boldsymbol{\theta})}{\boldsymbol{A}(z,\boldsymbol{\theta})} \text{ and } \hat{\boldsymbol{H}}(z,\boldsymbol{\theta}) = \frac{\boldsymbol{C}(z,\boldsymbol{\theta})}{\boldsymbol{A}(z,\boldsymbol{\theta})}, \quad \boldsymbol{\theta}^T = [\boldsymbol{\theta_a} \quad \boldsymbol{\theta_b} \quad \boldsymbol{\theta_c}]$$

where $\boldsymbol{\theta_a} = [a_1 \dots a_{na}]^{\boldsymbol{T}}$, $\boldsymbol{\theta_b} = [b_0 \dots b_{nb-1}]^{\boldsymbol{T}}$, $\boldsymbol{\theta_c} = [c_1 \dots c_{nc}]^{\boldsymbol{T}}$ are coefficients of the corresponding polynomials

$$\boldsymbol{B}(z,\boldsymbol{\theta}) = b_0 + b_1 z^{-1} + \cdots + b_{nb-1} z^{-nb+1}, \boldsymbol{A}(z,\boldsymbol{\theta}) = 1 + a_1 z^{-1} + \cdots + a_{na} z^{-na} \text{ and } \boldsymbol{C}(z,\boldsymbol{\theta}) = 1 + c_1 z^{-1} + \cdots + c_{nc} z^{-na}$$

*However, the desired parametrization for the monitoring problem of interest **should be** in terms of the damping coefficients and their corresponding frequencies*, $\hat{\zeta}_i(t)$ and $\hat{\omega}_i(t)$.

We need to parametrize the ARMAX model from $\boldsymbol{\theta}^T = [\boldsymbol{\theta_a} \quad \boldsymbol{\theta_b} \quad \boldsymbol{\theta_c}]$ to $\boldsymbol{\rho}^T = [\boldsymbol{\theta}_\zeta^T \quad \boldsymbol{\theta}_b \quad \boldsymbol{\theta}_c]$ as shown in *, where:

$$\boldsymbol{\theta}_\zeta^T = [\zeta_1 \quad \dots \quad \zeta_{ni} \quad \dots \quad \omega_{n,1} \quad \dots \quad \omega_{n,ni}]^{\boldsymbol{T}}$$

with $\boldsymbol{\theta}_\zeta^T$ having the same dimensions as $\boldsymbol{\theta_a}$. This implies that we can re-parametrize the original model $\mathcal{M}$ as $\mathcal{M}_{\boldsymbol{\rho}}$ where

$$\hat{\boldsymbol{G}}(z,\boldsymbol{\theta}) = \hat{\boldsymbol{G}}(z,\boldsymbol{\rho}) \text{ and } \hat{\boldsymbol{H}}(z,\boldsymbol{\theta}) = \hat{\boldsymbol{H}}(z,\boldsymbol{\rho})$$

with the new parameter vector $\boldsymbol{\rho}^T = [\boldsymbol{\theta}_\zeta^T \quad \boldsymbol{\theta}_b \quad \boldsymbol{\theta}_c]^T$.

Note: to perform this re-parameterization, * shows the procedure to compute $\hat{\boldsymbol{G}}(z,\boldsymbol{\rho})$ and $\hat{\boldsymbol{H}}(z,\boldsymbol{\rho})$. Observe this computation is not trivial. Analytical symbolic expressions for the computations are provided in *.

* S. Boersma, et al "Probing Signal Design for Enhanced Damping Estimation in Power Networks," International Journal of Electrical Power & Energy Systems, vol. 129, July 2021, 106640, ISSN 0142-0615

Optimal Probing Signal Design

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We adopt a multi-sine time-domain realization

$$\boldsymbol{u}(t) = \sum_{r=1}^{M} A_r \cos(\omega_r t + \varphi_r)$$

where A_r, ω_r, φ_r are the magnitude, frequency and phase of the r-th sine component from a total of M.

The power spectrum of the multi-sine is

$$\boldsymbol{\Phi_u}(\omega) = \frac{\pi}{2}\sum_{r=1}^{M} A_r^2\big(\delta(\omega-\omega_r)+\delta(\omega+\omega_r)\big)$$

with δ being the Dirac function.

Optimal Design, depends on the objectives of the identification problem:

- which in our case are to obtain a $\boldsymbol{u}(t)$ that **minimizes the controller effort, and**
- **a $\boldsymbol{y}(t)$ that min. the disturbances in the network,**
- **while at the same time ensuring a user-defined upper bound on the damping estimation's variance.**

Using the framework developed in ** we formulate the following optimization problem:

$$\min_{\boldsymbol{\Phi_u}(\omega)} \left(\frac{c_1}{2\pi}\int_{-\pi}^{\pi}\Phi_u(\omega)d\omega\right) + \left(\frac{c_2}{2\pi}\int_{-\pi}^{\pi}\Phi_y(\omega)d\omega\right)$$
$$s.t. \quad \text{variance}(\zeta_i) < \boldsymbol{\eta_i}, \text{for } i = 1,2,\dots,n_i$$

where:

$\boldsymbol{\Phi_u}(\omega)$ probing signal spectrum
$\boldsymbol{\Phi_y}(\omega)$ output signal spectrum
$\boldsymbol{\eta_i}$ user defined variance (upper bound)
c_1 and c_2 are weighting factors.

- *Minimizing the 1st term* results in minimal effort of the controller/actuators.
- *Minimizing the 2nd term results* in a probing signal that a spectrum without unnecessary excitation power at the frequencies of low damped models.
- A trade-off between these two terms must be made by tunning the weights c_1 and c_2.

** X. Bombois, G. Scorletti, M. Gevers, P.M.J. Van den Hof and R. Hildebrand, "Least costly identification experiment for control", Automatica, vol.42, no.10, pp.1651-1662, Oct. 2006.

*Optimal Design with upper η_i of $var(\zeta_i)$ (bound)**

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We rewrite the optimization problem using $\widehat{\boldsymbol{G}}(z,\boldsymbol{\rho})$ and $\widehat{\boldsymbol{H}}(z,\boldsymbol{\rho})$ for probing signal design, i.e., designing $\boldsymbol{u}(t)$.

$$\min \frac{c_1}{2}\sum_{r=1}^{M} A_r^2 + \frac{c_2}{2}\sum_{r=1}^{M} A_r^2 \left|\widehat{\boldsymbol{G}}(\omega_r,\boldsymbol{\rho})\right|^2,$$

$$\text{st} \quad \text{variance}(\zeta_i) < \boldsymbol{\eta}_i \quad \text{for } i = 1,2,\ldots,n_i$$

$$A_r^2 \geq 0, \quad \text{for } r = 1,2,\ldots,M$$

which adds the 2nd constraint to ensure positivity of the probing signal power.

Following the procedure to solve this problem from *, we obtain the solution to the optimal signal:

$$\boldsymbol{u}(t) = \sum_{r=1}^{M} A_r \cos(\omega_r t + \varphi_r)$$

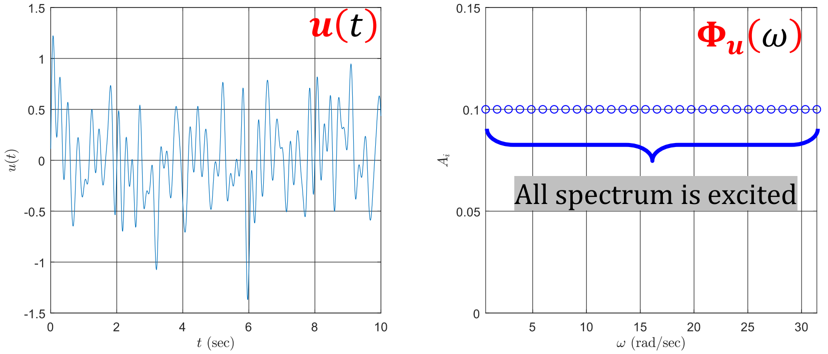
That means that the solution consists of:

- A_r found by optimization,
- ω_r defined in a grid of values, and
- φ_r is chosen randomly.

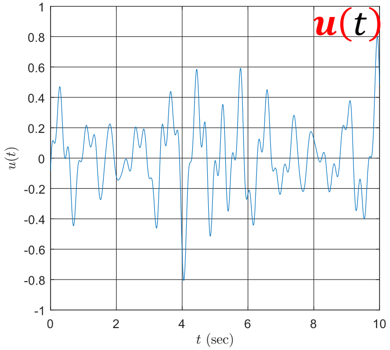
Note: this requires to evaluate the covariance matrix P_ρ, ***not trivial***. See * for the analytical expressions.

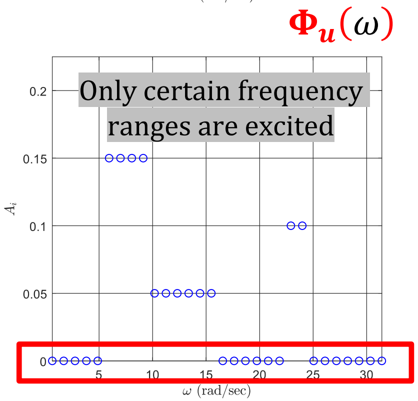
Comparison of potential input signals $\boldsymbol{u}(t)$:

- Conventional Multi-sine:



- Using proposed method





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* S. Boersma, et al "Probing Signal Design for Enhanced Damping Estimation in Power Networks," International Journal of Electrical Power & Energy Systems, vol. 129, July 2021, 106640, ISSN 0142-0615

Base and Optimal Procedure

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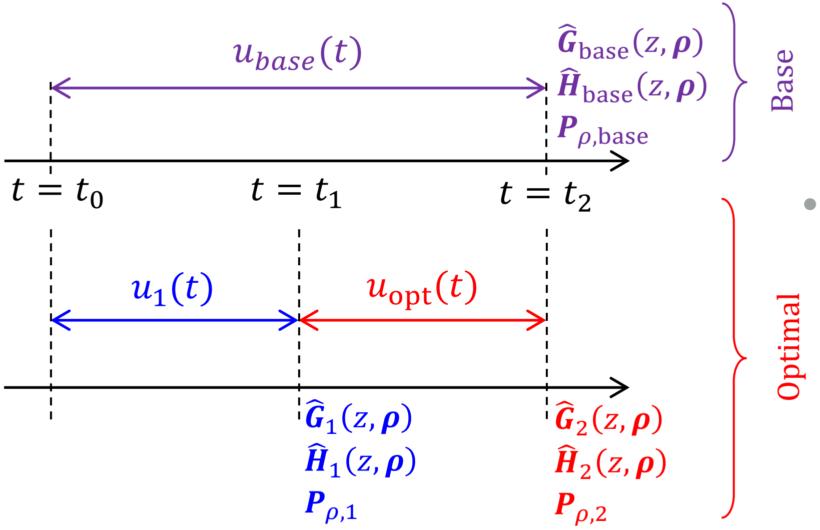


- **Base procedure:**
  - Defines a conventional probing signal $u_{base}(t)$ with linearly spaced $\omega_r \in [f_1 \quad f_2]$ and $r = M$
  - Perform sys.id. experiment using $t = [t_0, t_2]$ and collect measurements $y(t)$
  - Follow (*) to evaluate $\hat{G}_{\text{base}}(z,\boldsymbol{\rho})$ and $\hat{H}_{\text{base}}(z,\boldsymbol{\rho})$ and evaluate $\boldsymbol{P}_{\rho,\text{base}}$

- **Optimal procedure:**
  - Consists of two experiments.
  - The first experiment follows the same approach as the base procedure, with $u_1(t) = u_{base}(t)$
  - We use the **base** and the first experiment to determine the user defined variance by calculating:

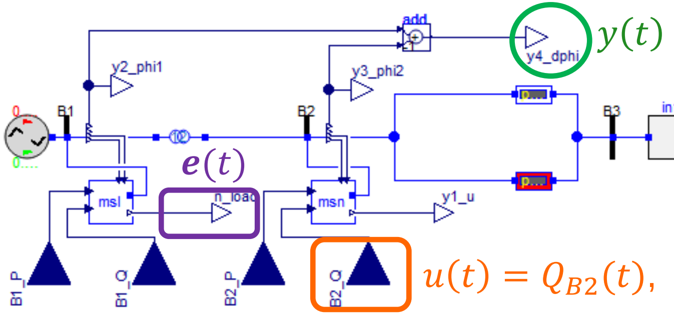
$$\eta_i^{-1} = \left(e_i^T P_{\rho,\text{base}} e_i\right)^{-1} - \left(e_i^T P_{\rho,1} e_i\right)^{-1}$$

  - This assures that the optimal input signal spectrum, $\boldsymbol{\Phi_u}(\omega)$, has a lower spectral power.
  - The second experiment applies the optimal signal $u_{\text{opt}}(t)$ designed through the optimization problem defined in the previous slide.

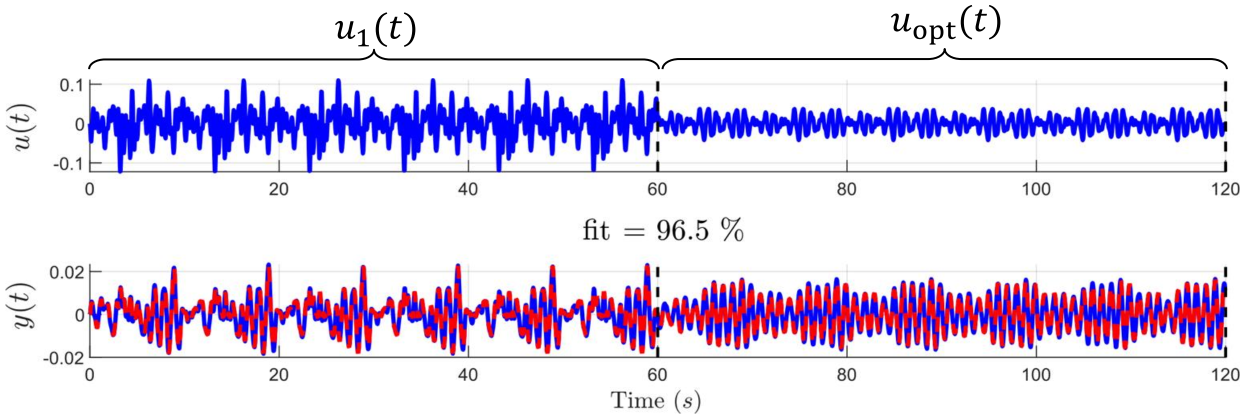
Single-Machine Infinite Bus (SMIB): Case 1

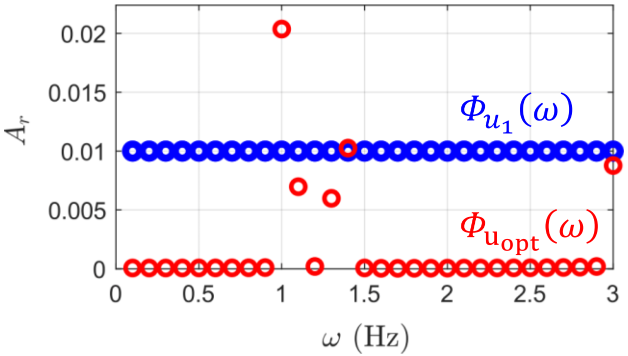
Case 1: $c_1 = 1$ and $c_2 = 0$

- Deviation from nominal operating condition of 2%
- Estimates:
  - 1 Hz (true 1.1) with damping of 0.082 (true 0.079)
- Fit of 96.5%, cross-validation between batches is 89.6%
- Power in $y(t)$:
  - $u_{\text{opt}}(t)$ batch is 20% higher than in $u_1(t)$ batch.
- **Note:** illustrative, small *N* for only 2 min.



Main mode: 1.1 Hz and 0.079 damping.
$u(t) = Q_{B2}(t)$, (e.g., STATCOM) and $y(t)$ is the angle difference between buses 1 and 2, $e(t)$ is the random load connected at bus 1.

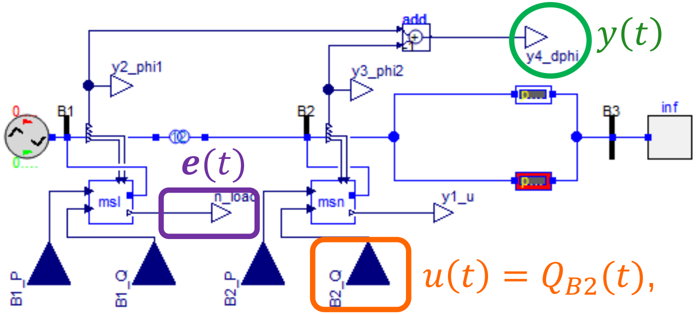




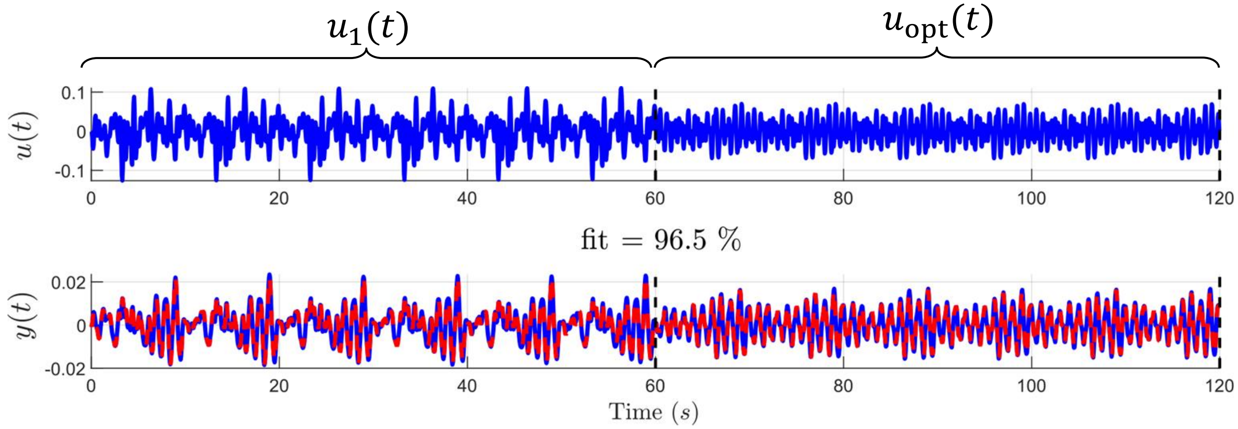
Single-Machine Infinite Bus (smib): Case 2

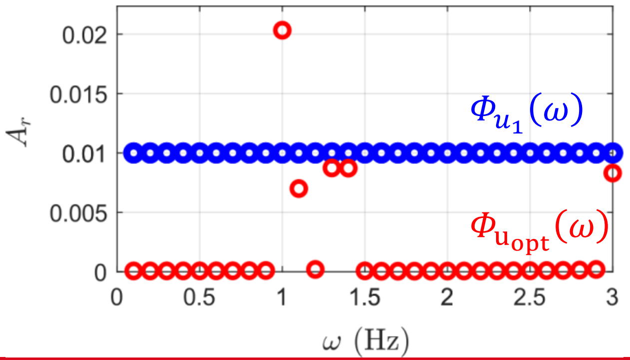
Case 2: $c_1 = 1$ and $c_2 = 1000$

- Estimates:
  - 1 Hz (true 1.1) with damping of 0.080 (true 0.079)
- Fit of 96.5%, cross-validation between batches is 90.7%
- Power in $y(t)$:
  - $u_{\text{opt}}(t)$ batch is ***40% lower*** than in $u_1(t)$ batch.
- **Substantial decrease in $y(t)$ power → reduced power system impact.**



Main mode: 1.1 Hz and 0.079 damping.
$u(t) = Q_{B2}(t)$, (e.g., STATCOM) and $y(t)$ is the angle difference between buses 1 and 2, $e(t)$ is the random load connected at bus 1.

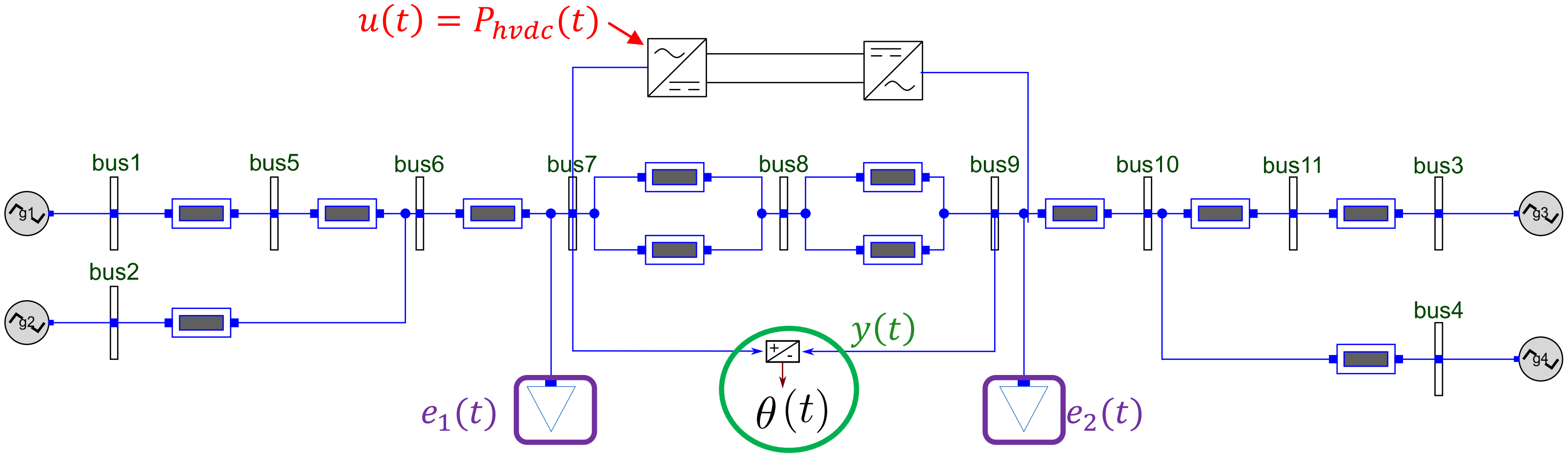




Kundur-Klein-Rogers (KKR) with VSC-HVDC Case Studies

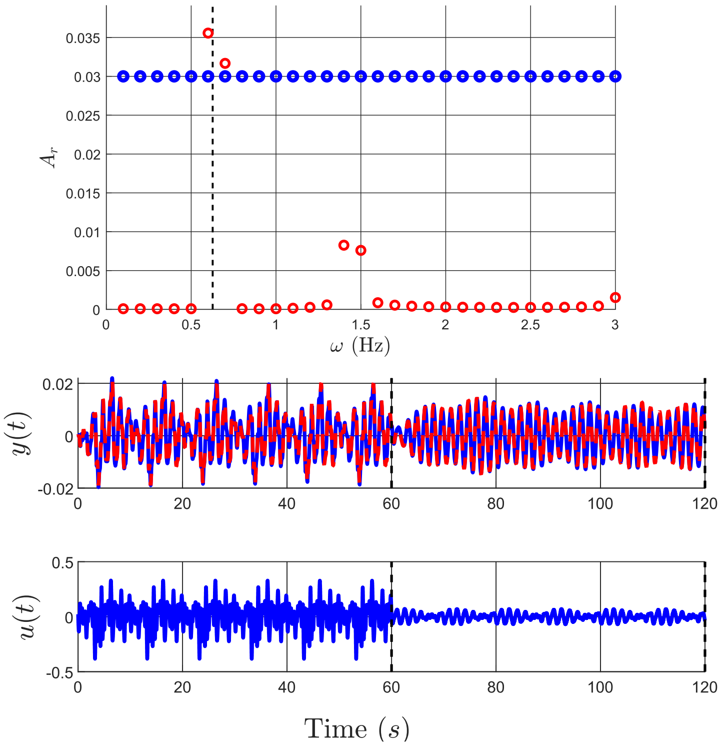
- ***True System*** Modelica model of the KKR model with and embedded VSC-HVDC link.
  Mode of interest: inter-area with $\omega_{true} = 0.63\ Hz$ and $\zeta_{true} = 0.015$, we only set a bound on the damping estimate variance for this mode. (Other modes are 1.1 and 1.3 Hz)

- Probing signal: $u(t) = P_{hvdc}(t)$ (power through the HVDC link)
- Measurements: $y(t) = \theta(t) = \measuredangle\tilde{V}_{bus7} - \measuredangle\tilde{V}_{bus9}$ (angle difference from PMUs)
- Random loads at Buses 7 and 9: $\boldsymbol{e}(t)$ white noise with standard deviation 5×10^{-4}

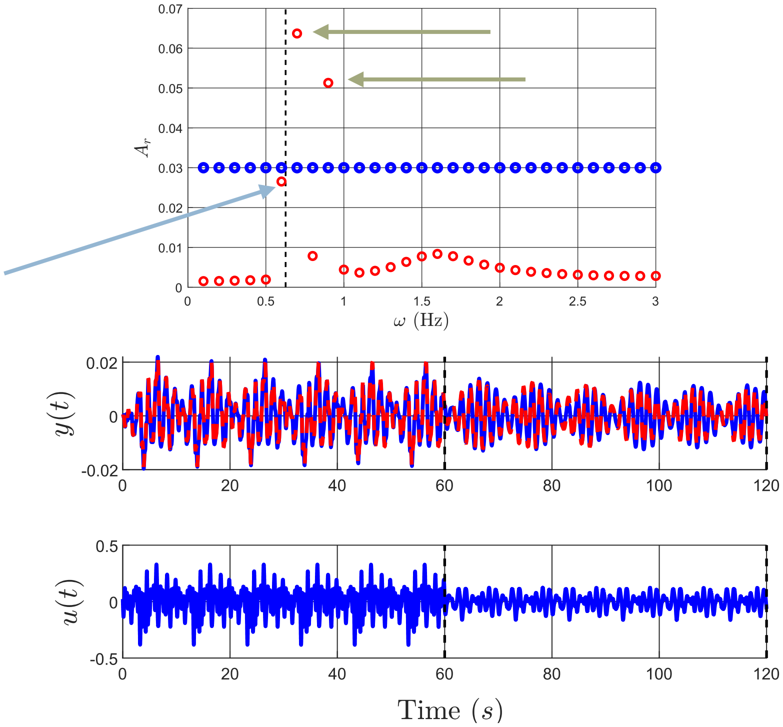


Optimal Design Results

Case 1: $c_1 = 1$ and $c_2 = 0$



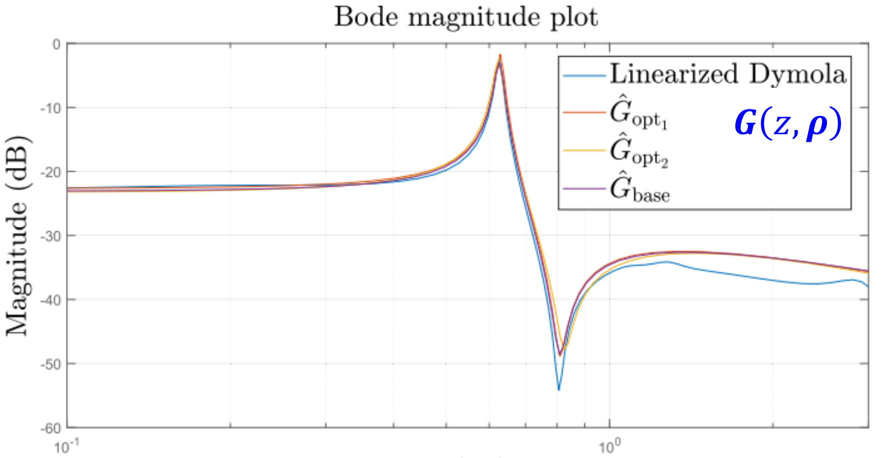
Case 2: $c_1 = 0.5$ and $c_2 = 2500$



Quality Measures

Bode Plots:

- *True System* can be linearized using Dymola/Modelica software, allows to compare
  - $\hat{G}_{\text{base}}(z,\boldsymbol{\rho})$, $\hat{G}_{\text{opt1}}(z,\boldsymbol{\rho})$ (case 1) and $\hat{G}_{\text{opt2}}(z,\boldsymbol{\rho})$ (case 2) with the true $\boldsymbol{G}(z,\boldsymbol{\rho})$
- The dominant characteristics are captured well by identified models, but not the other modes.
- Why?
  - Identified models contain only 4 poles, while the true system has 46.



Sample mean and variance of the damping estimates and normalized signal powers

- *100* Monte Carlo non-linear time-domain simulations are conducted, and damping estimates are obtained for all three cases.

Procedure	Mean	Variance	Normalized Probing Signal Power	Normalized Measurement Power
Base Procedure	0.018	4.6×10^{-7}	1.00	1.00
Optimal Proc. 1	0.016	18.0×10^{-7}	0.10	0.85
Optimal Proc. 2	0.017	9.9×10^{-7}	0.30	0.60

Note: see Sjoerd's paper with a larger system model example, Nordic 44.

Real-Time Prototyping using Modelica and the FMI: Needs

- *In the absence of a real system to perform experiments on, first principal physics-based models are indispensable* to develop, validate and even test probing design techniques → they provide "the ground truth".

- However, **power system simulation models** have several drawbacks:
  - ***Are locked-in a specific tool*** (e.g., PSS/E), i.e., they are usually NOT portable (cannot fully manipulate the model in different environments).
  - Most simulators **do not have symbolic linearization facilities** to obtain the "true" system modes, requires model re-implementation from scratch (e.g., MATLAB PST, PSAT, etc.)
  - Moreover, these simulators **cannot be used for testing hardware**-based realization of input signal device and/or controller.

- This adds complexity in bringing the "probing approach" to practice beyond research.

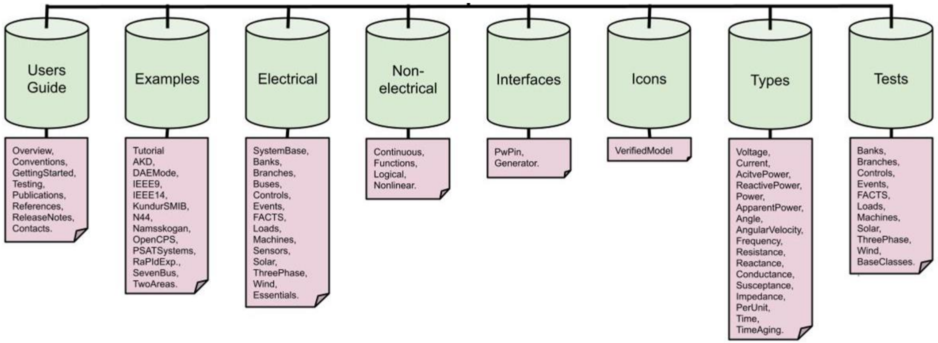
- We propose an approach to address these issues, the **adoption of interoperable open-access standards** for modeling and simulation, **Modelica and the FMI**:
  - ***Modelica:*** equation-based object-oriented modeling language for cyber-physical systems, NOT a tool, and is supported by more than 9 tools – https://www.modelica.org
  - ***The Functional Mock-up Interface Standard:*** allows to export/import models with a common interface into more than 150 tools, for different purposes - https://fmi-standard.org/tools/

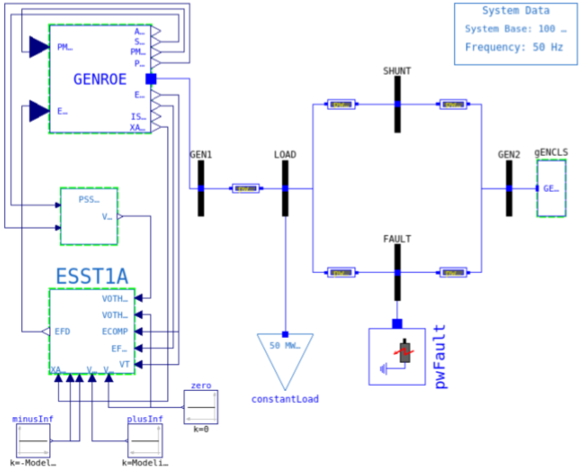
- What does this enable?

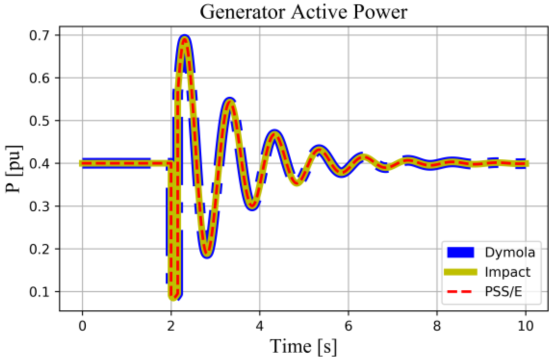
A single model across multiple analysis purposes.

OpenIPSL: Power System Modeling and Analysis

- OpenIPSL is an open-source Modelica library with a large number of component models validated against PSS/E, http://www.openipsl.org





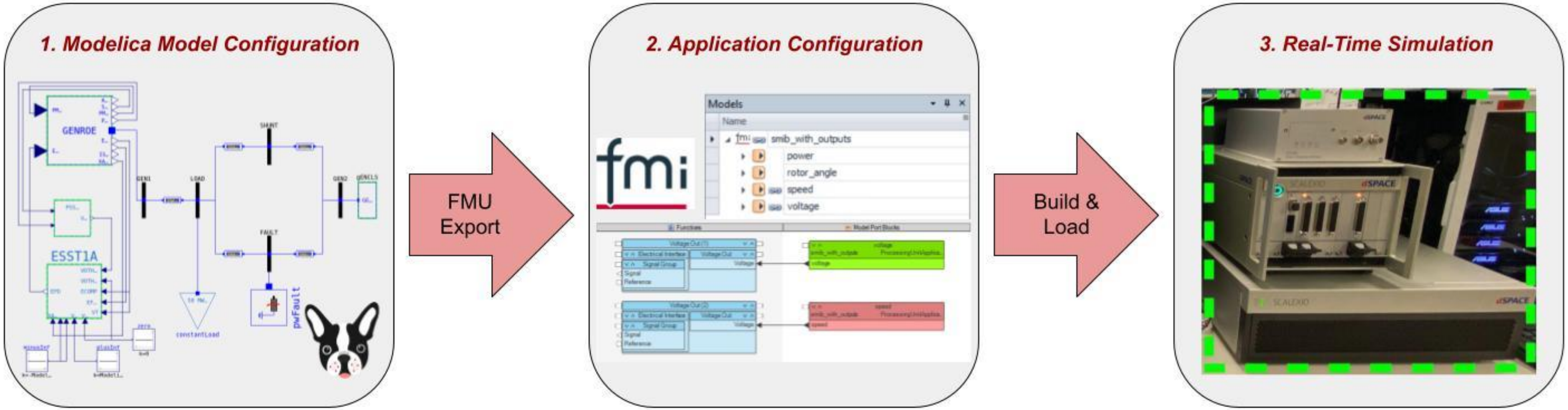


- Validated to produce the **same** simulation results among **5 different** Modelica tools for Non-Linear Time-Domain Simulation
- Symbolic Linearization supported by Modelica tools.
- Model transformation to support moving from PSS/E or CIM to Modelica: https://alsetlab.github.io/NYPAModelTransformation/

Real-Time Simulation using the FMI

Framework description

1. Offline power system model is assembled in Modelica using the Dymola, and outputs for taking measurements.
2. An FMU is created using the Modelica model is loaded into dSPACE software for output and input configuration.
3. Model is built and loaded into real-time simulator, a dSPACE SCALEXIO, and I/O board is used to read outputs.



*** FMU = Functional Mock-up Unit,** a model exported according to the FMI standard specification.

Real-Time Simulation for Probing Experiment Prototyping

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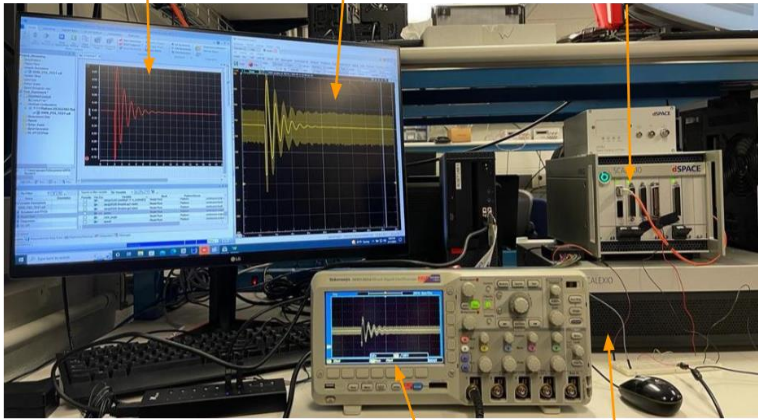
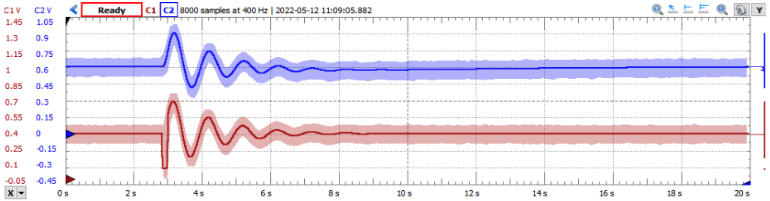
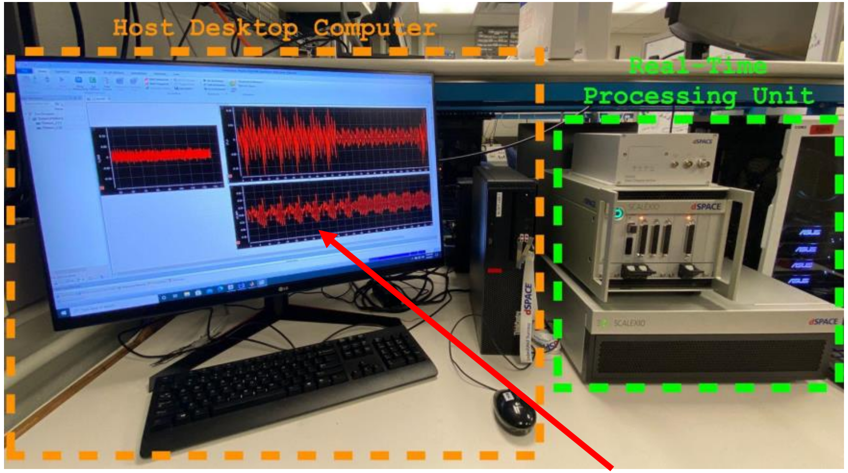
Real-Time Simulation





Red: generator's electrical power output; Blue: generator's rotor angle.

Probing Experiment Design Prototyping



Probing Signal and Measured Response

- *Surprise:* used for probing input signal designed in SMIB study!
- Proposed approach:
  - Design one model, from offline to RT testing;
  - Probing signal is optimized and tested in RT before implementation in field.
  - Address issues related to real-world realization and real-time response before field trials.

Conclusions and Future Work

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- Probing signals can be effectively designed to provide an optimal signal that:
  - Has a **power spectrum** that that **minimizes the disturbances in the network, while at the same time ensuring a (user-defined) upper bound on the damping estimation's variance.**
  - This is achieved by reparameterization of an ARMAX model structure with parameters the oscillation mode characteristics, $\hat{\boldsymbol{\zeta}}_{\boldsymbol{i}}(\boldsymbol{t})$ and $\hat{\boldsymbol{\omega}}_{\boldsymbol{i}}(\boldsymbol{t})$, and the computation of $\widehat{\boldsymbol{G}}(z,\boldsymbol{\rho})$, $\widehat{\boldsymbol{H}}(z,\boldsymbol{\rho})$ and the covariance matrix P_{ρ}.
  - **These are used to solve optimization problem that characterizes the input signal** $\boldsymbol{u}(t) = \sum_{r=1}^{M} A_r \cos(\omega_r t + \varphi_r)$ by finding A_r, ω_r defined in a grid of values, and φ_r *is chosen randomly*.
- Proposed approach offers unique advantage in allowing to have more design options for $\boldsymbol{u}(t)$, providing the best trade of between:
  - The effort of the controller/actuator that drives $\boldsymbol{u}(t)$ into the system, and
  - The impact on the system, a $\boldsymbol{u}(t)$ with no (unnecessary) excitation at frequencies close to low damped modes.
  - Method can be extended to optimize φ_r also.
  - Such improvements can help steering the power industry to potentially allow to perform probing in more regular basis!
- Interoperable open-access modeling and simulation standards, Modelica and FMI, and the OpenIPSL library:
  - The ability to go from off-line design to real-time prototyping of probing signals is greatly facilitated thanks to.
  - This will become more important to for probing design of Inverter-Based Renewable Energy sources and other power-electronic based devices with dynamics in a broader spectral range and oscillatory modes in the 100s and 1,000s of Hz.
- Current collaboration with Dr. Xavier Bombois focuses on exploiting the least costly experiment design framework to obtain high-quality identified models for PSS control re-design when the system's damping changes for the case of the PSS in synchronous machines: https://hal.archives-ouvertes.fr/hal-03708303

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Thank you and Merci!

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