NTNU
Norwegian University of
Science and Technology

Frequency control and stability requirements on hydro power plants

Sigurd Hofsmo Jakobsen
Department of electrical engineering

October 17, 2019

Outline

Problem

Paper I

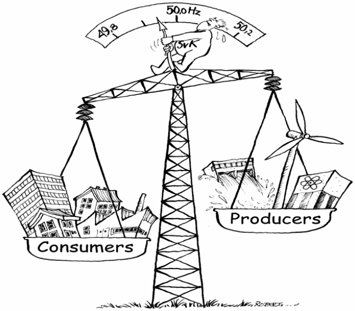
Paper II

Paper III

Paper IV

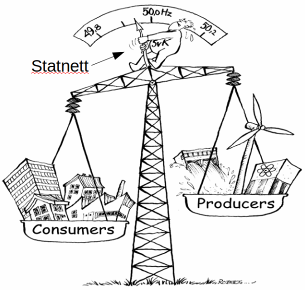
Load and production balancing

— The power system frequency measures the power balance.



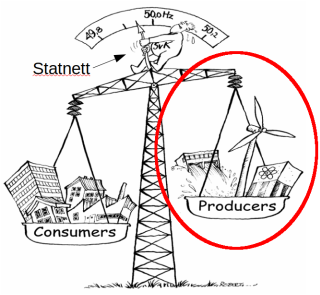
Load and production balancing

- The power system frequency measures the power balance.
- It is the responsibility of Statnett to control the frequency.



Load and production balancing

- The power system frequency measures the power balance.
- It is the responsibility of Statnett to control the frequency.
- However, it is the power plant owners who can control the frequency.



Buying frequency control

— Statnett pays all power plant owners to provide frequency control.

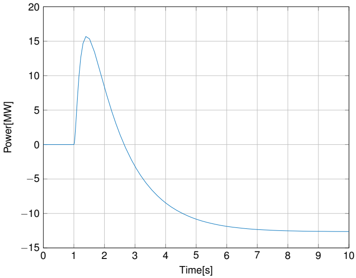


Figure: Frequency control response to step change in frequency

Buying frequency control

— Statnett pays all power plant owners to provide frequency control.
— However, they don't provide the same quality of service.

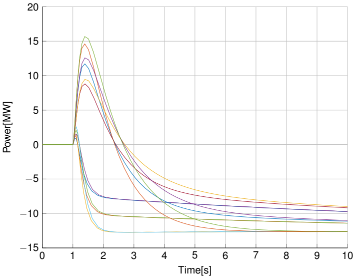


Figure: Frequency control response to step change in frequency

Buying frequency control

- Statnett pays all power plant owners to provide frequency control.
- However, they don't provide the same quality of service.
- Renewable energy sources such as wind and solar don't contribute.

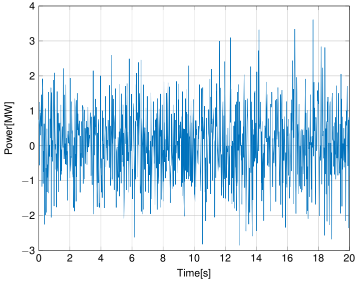


Figure: Frequency control response to step change in frequency

Future of frequency control

— Power plants have to pass tests to get paid to provide frequency control.

— Only those who pass the tests get paid for the service.

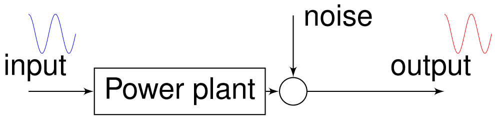
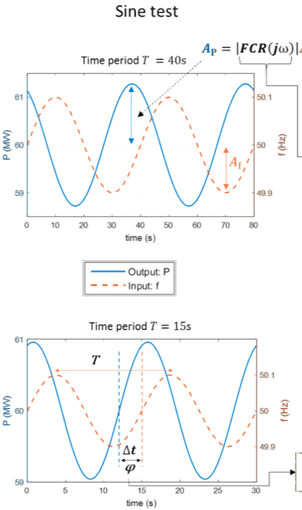


Figure: Test of power plant

Tests proposed by the industry



Sine tests are used to find out gain and phase at discrete time periods which in turn can be used to construct a Bode plot

$F(j\omega)$ = normalized $\mathbf{FCR}(j\omega)$, i.e. $|F(j0)| = 1.00$pu

T (s)	Gain $\|F(j\omega)\|$ (p.u.)	Phase Arg($F(j\omega)$) (°)
10	0.10	57
15	0.12	72
25	0.15	112
40	0.16	117
50	0.20	120
60	0.21	123
70	0.22	126
90	0.27	132
150	0.32	143
300	0.55	146

$$\varphi = \text{Arg}(\text{F}(j\omega)) = \Delta t \frac{360°}{T}$$

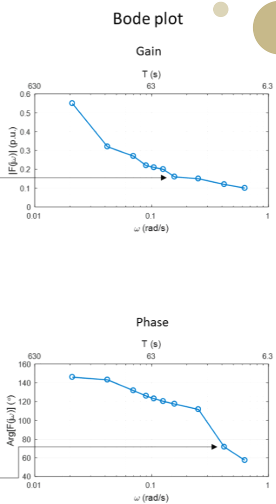
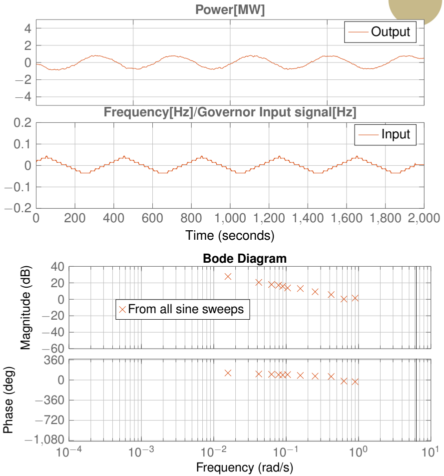


Figure: Testing procedure [source:ENTSO-E]

Example from real tests

- The power plant needs to be disconnected
- Takes up to 20 hours.

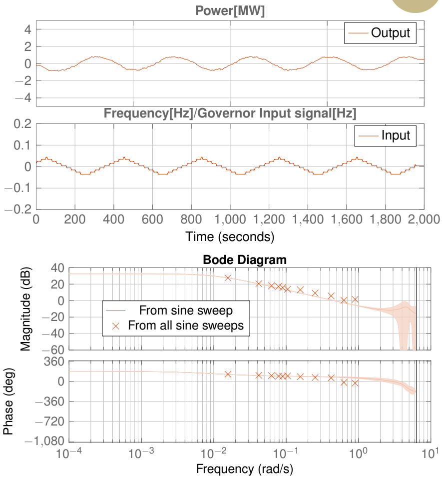


Example from real tests

— The power plant needs to be disconnected

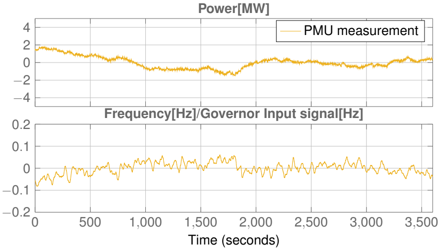
— Takes up to 20 hours.

— Only one sine test needed with model learning.



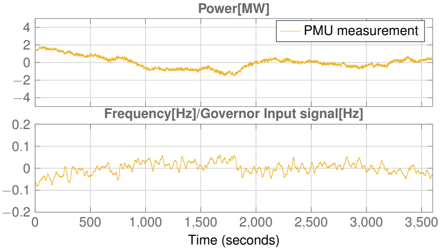
Motivation

— The power system is never really in steady state.



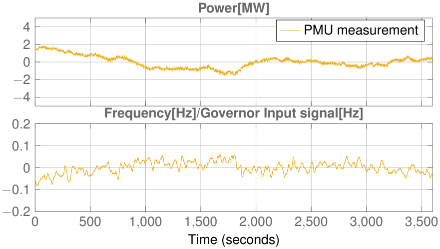
Motivation

- The power system is never really in steady state.
- Can the power plant dynamics be identified from normal operation measurements?



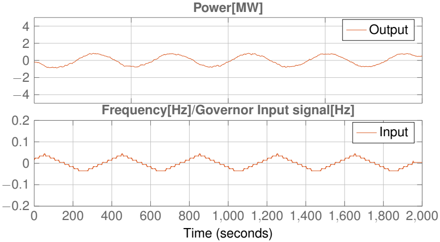
Research questions

— Can power plant dynamics be identified using a PMU?



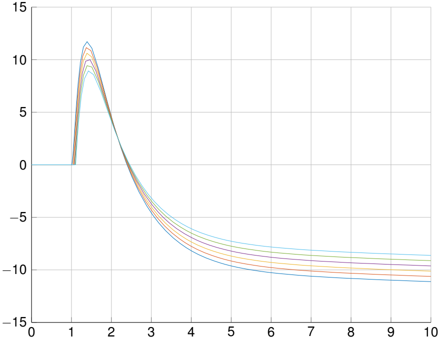
Research questions

- Can power plant dynamics be identified using a PMU?
- Can power plant dynamics be identified using control system measurements without disturbing the operation of the plant?



Research questions

- Can power plant dynamics be identified using a PMU?
- Can power plant dynamics be identified using control system measurements without disturbing the operation of the plant?
- What is the effect of nonlinearities on the identification?



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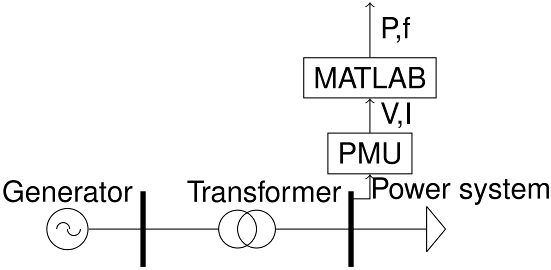
Background

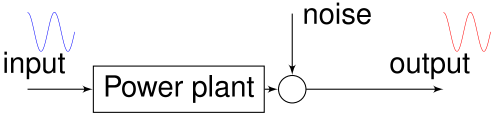
— Idea from[1] can the power plant dynamics be identified using PMUs



[1] Dinh Thuc Duong et al. "Estimation of Hydro Turbine-Governor's Transfer Function from PMU Measurements". In: IEEE PES General Meeting. Boston: IEEE, July 2016

Background

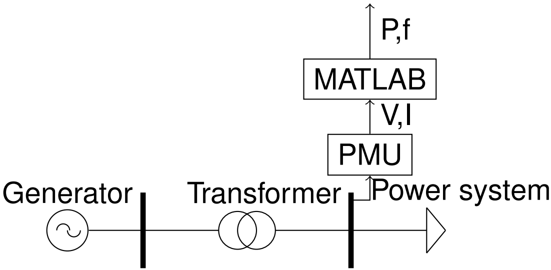
- Idea from[1] can the power plant dynamics be identified using PMUs
- Uses the same input and output measurements as in the requirements:
  - Input: Power system frequency.
  - Output: Electric power.



[1] Dinh Thuc Duong et al. "Estimation of Hydro Turbine-Governor's Transfer Function from PMU Measurements". In: IEEE PES General Meeting. Boston: IEEE, July 2016

Methodology

- Collect several datasets from PMUs.
- Calculate power and frequency from the measurements.
- Identify dynamics using vector fitting.
- Compare models.



Vector fitting basics

$$Y(s) = H(s) \cdot U(s) \tag{1}$$

— Vector fitting fits a transfer function to measured input and output data

Vector fitting basics

- Vector fitting fits a transfer function to measured input and output data
- It assumes the system to have the following structure.

$$Y(s) = H(s) \cdot U(s) \tag{1}$$

$$H(s) = d + \sum_{i=1}^{n_p} \frac{r_i}{s - p_i} \tag{2}$$

Vector fitting basics

- Vector fitting fits a transfer function to measured input and output data
- It assumes the system to have the following structure.
- In time domain it is.

$$Y(s) = H(s) \cdot U(s) \tag{1}$$

$$H(s) = d + \sum_{i=1}^{n_p} \frac{r_i}{s - p_i} \tag{2}$$

$$y(t) \approx \tilde{d}x(t) + \sum_{i=1}^{n_p} \tilde{r}_i x_i - \sum_{i=1}^{n_p} \tilde{k}_i y_i \tag{3}$$

$$x_i = \int_0^t e^{\tilde{p}_i(t-\tau)} x_i(\tau) d\tau \tag{4}$$

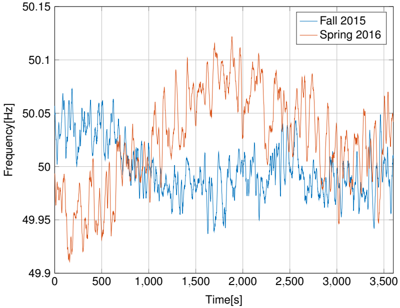
$$y_i = \int_0^t e^{\tilde{p}_i(t-\tau)} y_i(\tau) d\tau \tag{5}$$

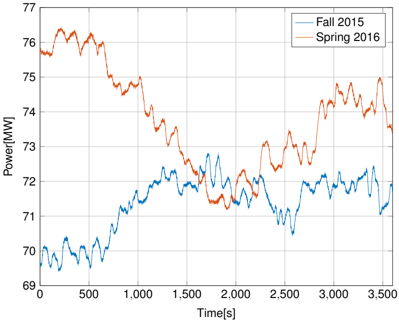
Vector fitting basics ctd.

— Find $\tilde{d}$, $\tilde{r}_i$ and $\tilde{k}_i$ to minimize:

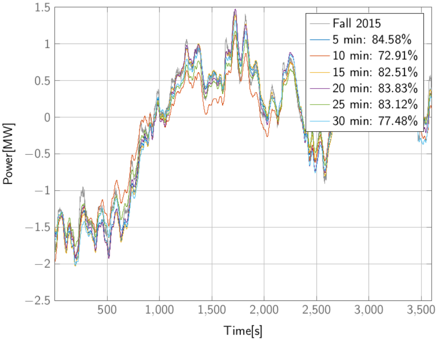
$$y(t) - (\tilde{d}x(t) + \sum_{i=1}^{n_p} \tilde{r}_i x_i - \sum_{i=1}^{n_p} \tilde{k}_i y_i) \tag{6}$$

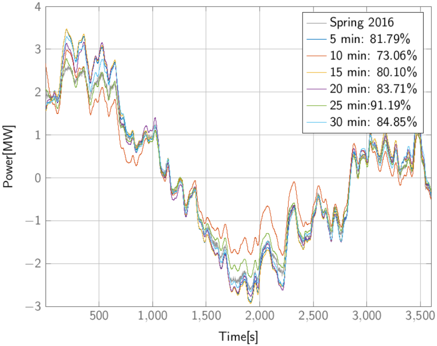
Cross validation using distant data sets



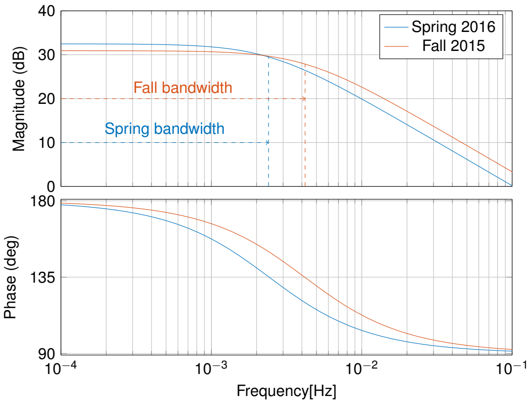


Cross validation using distant data sets





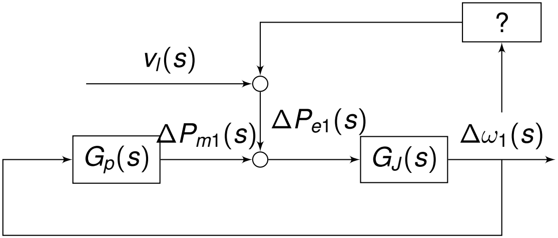
Estimated droop and bandwidth



Dataset	Droop[%]	Bandwidth[mHz]
Fall 2015	10	4.16
Spring 2016	8	2.41

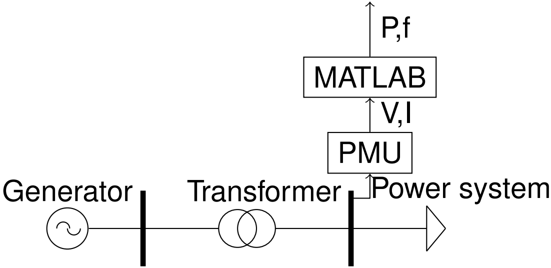
Shortcoming with the paper

- No theoretical validation of the results.
- No simulation validation of the results.



Main contributions to the research questions

- Promising results for 19 datasets.



Main contributions to the research questions

- Promising results for 19 datasets.
- Developed code for interfacing with the PMU data.

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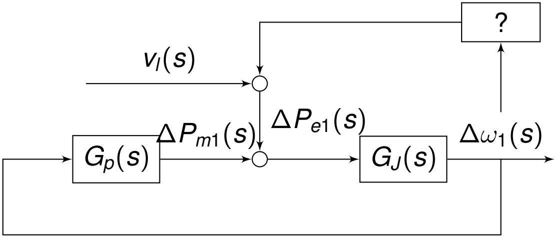
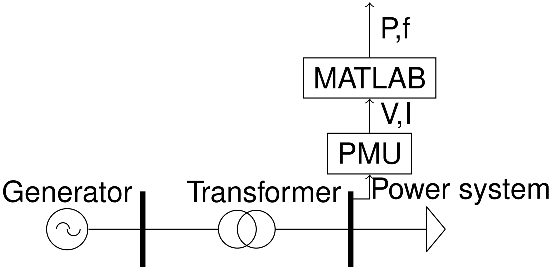
Motivation

- Explain the problem to my co-supervisor.
- Create a model for analysing the identifiability of hydro power plant dynamics.



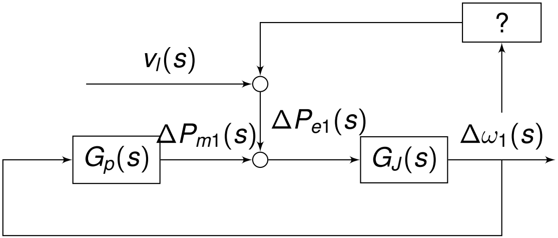
What do we need to model?

- From the PMU we get



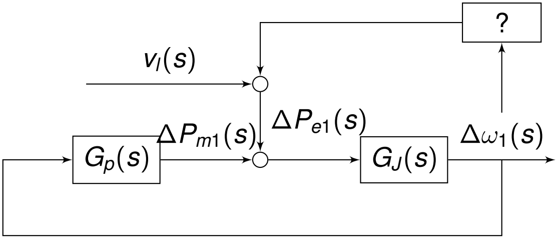
What do we need to model?

— From the PMU we get
  - Power: $\Delta P_{e1}(s)$.



What do we need to model?

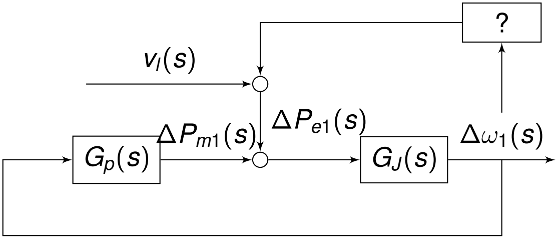
- From the PMU we get
  - Power: $\Delta P_{e1}(s)$.
  - Frequency: $\Delta f(s)$.



What do we need to model?

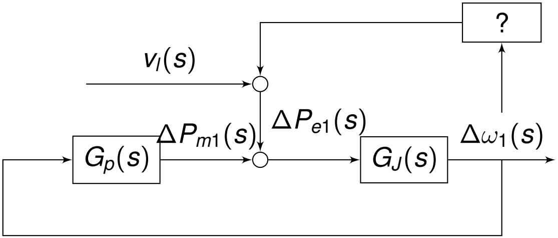
— From the PMU we get
  - Power: $\Delta P_{e1}(s)$.
  - Frequency: $\Delta f(s)$.

— We need to model how $\Delta P_{e1}(s)$ and $\Delta f(s)$ is related through the power system.



What do we need to model?

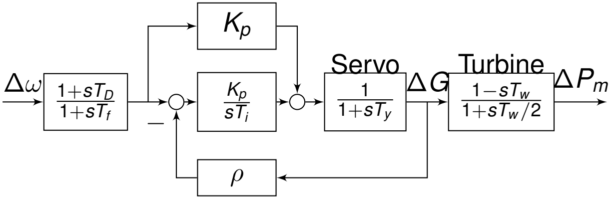
- From the PMU we get
  - Power: $\Delta P_{e1}(s)$.
  - Frequency: $\Delta f(s)$.
- We need to model how $\Delta P_{e1}(s)$ and $\Delta f(s)$ is related through the power system.
- We also need to model the power plant consisting of $G_p(s)$ and $G_J(s)$.



Power plant model

- Model for $G_p(s)$
- Model for $G_J(s)$

$$G_J(s) = \frac{1}{2Hs + K_d} \tag{7}$$



Power system model

— The frequency and power system angle is related.

$$\Delta\theta(s) = \frac{2\pi f_s}{s} f(s) \tag{8}$$

Power system model

- The frequency and power system angle is related.
- The angle and power is related.

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$$P_k \approx \sum_{m \in \Omega_k} x_{km}^{-1} \theta_{km} \tag{9}$$

Power system model

- The frequency and power system angle is related.
- The angle and power is related.
- On matrix form.

$$\Delta\theta(s) = \frac{2\pi f_s}{s} f(s) \tag{8}$$

$$P_k \approx \sum_{m \in \Omega_k} x_{km}^{-1} \theta_{km} \tag{9}$$

$$\mathbf{P} = \mathbf{Y}\theta \tag{10}$$

Power system model

- The frequency and power system angle is related.
- The angle and power is related.
- On matrix form.
- In software

$$\Delta\theta(s) = \frac{2\pi f_s}{s} f(s) \tag{8}$$

$$P_k \approx \sum_{m \in \Omega_k} x_{km}^{-1} \theta_{km} \tag{9}$$

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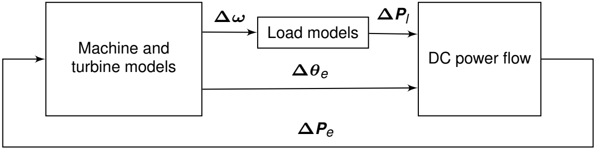


Test system

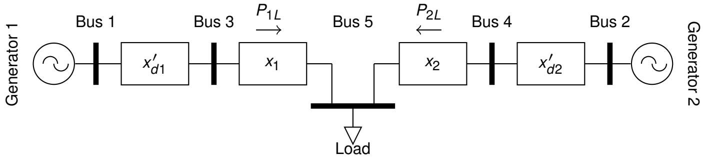
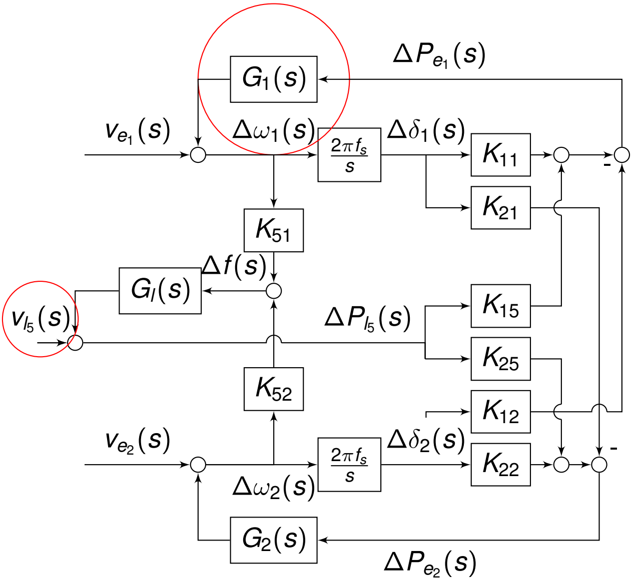


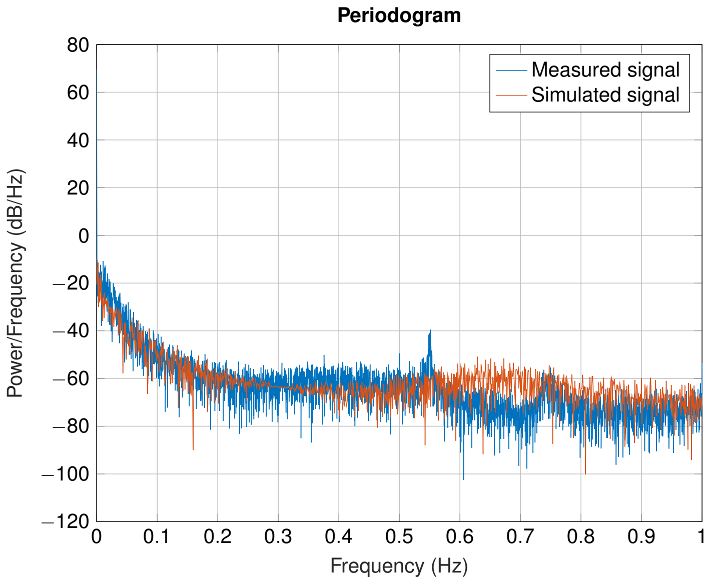
Figure: Single line diagram

Test system



$G_1(s)$
$\Delta P_{e_1}(s)$
$v_{e_1}(s)$
$\Delta\omega_1(s)$
$\frac{2\pi f_s}{s}$
$\Delta\delta_1(s)$
K_{11}
K_{21}
K_{51}
$\Delta f(s)$
$G_l(s)$
$v_{l_5}(s)$
$\Delta P_{l_5}(s)$
K_{15}
K_{25}
K_{52}
K_{12}
$v_{e_2}(s)$
$\frac{2\pi f_s}{s}$
$\Delta\delta_2(s)$
K_{22}
$\Delta\omega_2(s)$
$G_2(s)$
$\Delta P_{e_2}(s)$
-
-

Simulation Result



Main contributions

- Developed simple test system for analysing power plant identifiability using PMUs.
- Developed simple test system used in the proceeding papers for simulations.

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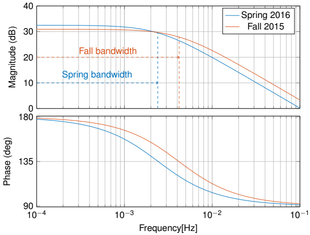
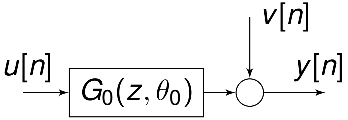
Background

— Why do we get different results?



Background

- Why do we get different results?
- The signals we use are corrupted by noise.



Background

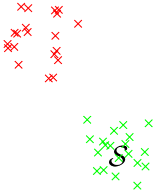
- Why do we get different results?
- The signals we use are corrupted by noise.
- From system identification we have that the error will be asymptotic normally distributed

$$\sqrt{N}(\hat{\theta}_n - \theta^*) \in AsN(0, P_\theta)$$

Background

- Why do we get different results?
- The signals we use are corrupted by noise.
- From system identification we have that the error will be asymptotic normally distributed
- However, first we need to prove the identifiability of the system

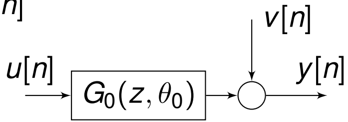
True system: $\mathcal{S}$
x: unbiased
x: biased



System identification basic

- Assume that a data set $Z^N = \{u[n], y[n] | n = 1 \dots N\}$ has been collected.
- The dataset Z^N is assumed generated by

$$\mathcal{S} : y[n] = G_0(z, \theta_0)u[n] + H_0(z, \theta_0)e[n] \tag{11}$$



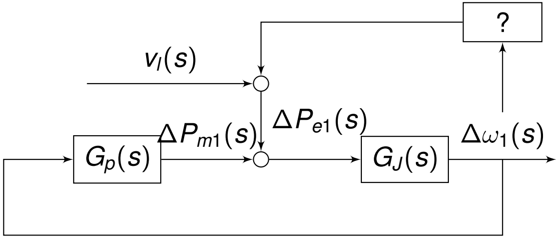
- Using the data set Z^N we want to find the parameter vector θ^N minimizing

$$\hat{\theta}_N = \arg\min_{\theta} \frac{1}{N} \sum_{n=1}^{N} \epsilon^2(n, \theta) \tag{12}$$

Modeling used for the validation

— The system we are identifying

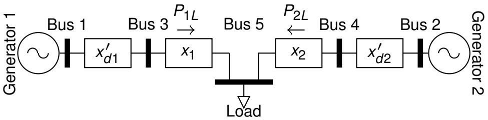
$$G_1(s) = \frac{G_p(s)}{1 + G_p(s)G_J(s)} \tag{13}$$



Modeling used for the validation

- The system we are identifying
- We use a small power system

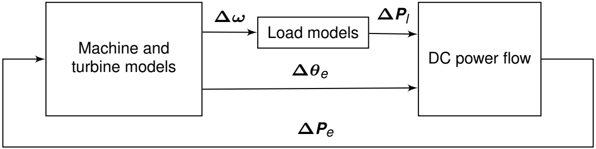
(13)



Modeling used for the validation

- The system we are identifying
- We use a small power system
- We use a dc power flow

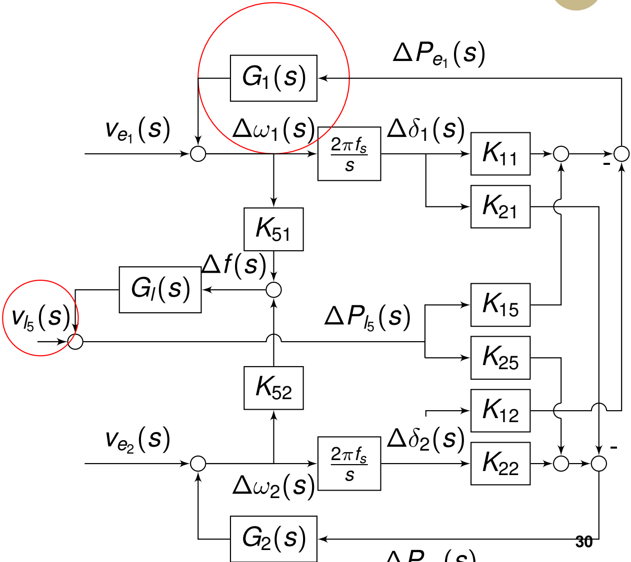
(13)



Modeling used for the validation

(13)

- The system we are identifying
- We use a small power system
- We use a dc power flow
- This results in the following block diagram



Results from the theoretical validation

— A consistent estimate of the closed loop transfer function of the turbine and electromechanical dynamics can be obtained by using:

Results from the theoretical validation

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- Measured PMU frequency as the output $u[n]$

Results from the theoretical validation

— A consistent estimate of the closed loop transfer function of the turbine and electromechanical dynamics can be obtained by using:

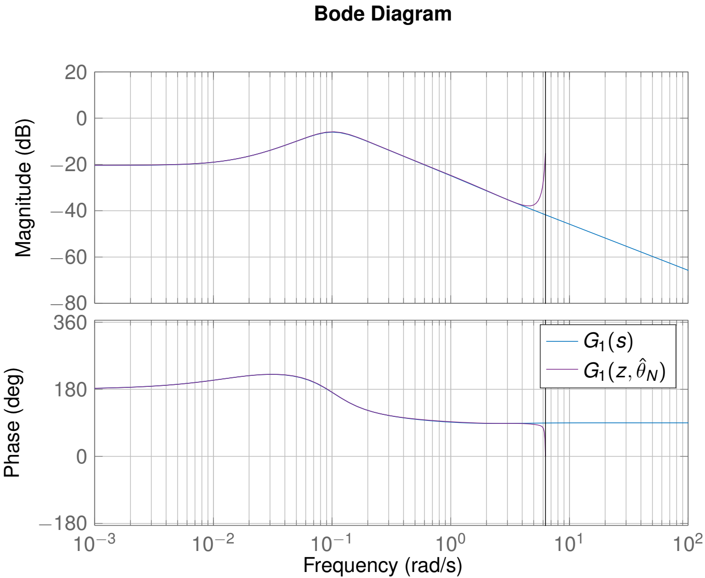
- Measured PMU frequency as the output $u[n]$
- Measured PMU power as the input $y[n]$

Results from the theoretical validation

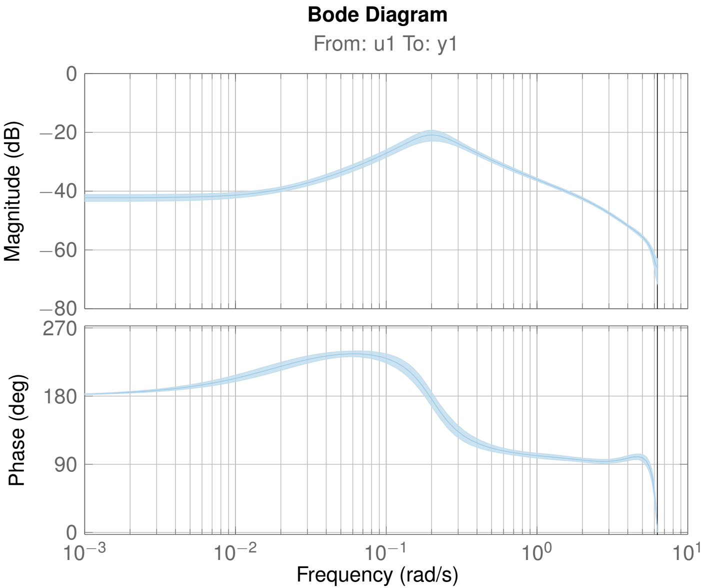
— A consistent estimate of the closed loop transfer function of the turbine and electromechanical dynamics can be obtained by using:
  - Measured PMU frequency as the output $u[n]$
  - Measured PMU power as the input $y[n]$

— The proof was done with the following assumptions.
  - The system is excited by a load acting as a filtered white noise process
  - The measurement error of the electrical power is negligible.
  - The measured frequency is a good estimate of the generator speed.

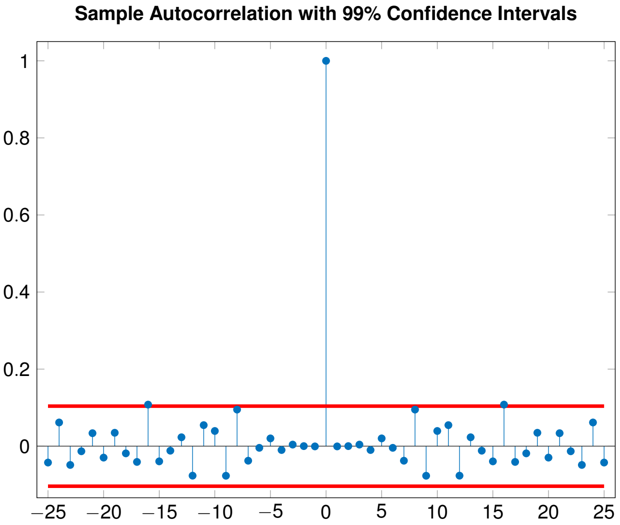
Comparison of bode plots from simulation



Model obtained using PMU data



Whiteness test on model identified using PMU data



Main contributions

- To show that the transfer function one is identifying using PMUs is $G_1(s)$.
- To prove under which conditions a consistent estimate of $G_1(s)$ is possible.
- To demonstrate the theory for identification of $G_1(s)$ on real datasets.

Outline

Problem

Paper I

Paper II

Paper III

Paper IV

Motivation

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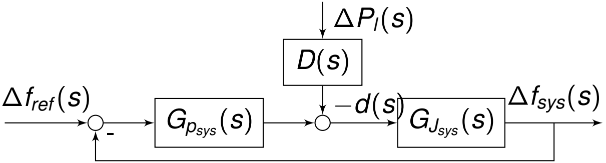
- Test the methods on more real datasets.
- Demonstrate that industry proposed tests can be done easier.
- Less theoretical presentation in a more industry focused conference.

The new requirements

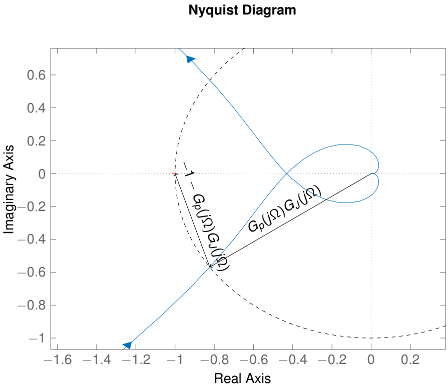
— Puts requirements on an aggregated system model.



The new requirements

- Puts requirements on an aggregated system model.
- Stability requirement

$$M_s = \max \left| \frac{1}{1 + G_p(j\Omega) G_J(j\Omega)} \right| = \max |S(j\Omega)| \tag{14}$$



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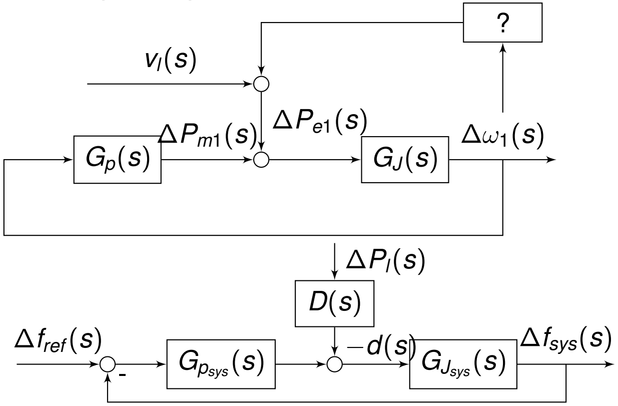
- Requirement per plant stated using a per unit conversion

Alternative requirements

— Place requirements directly on one power plant.



Alternative requirements

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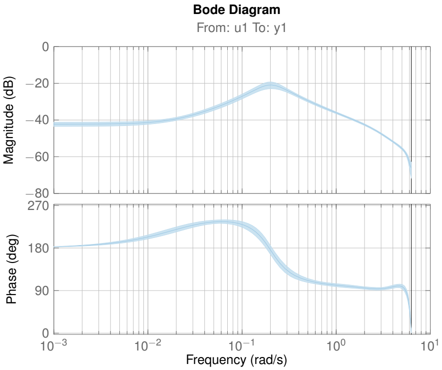

Alternative requirements

- Place requirements directly on one power plant.
- We already have an estimate of $G_1(s)$.
- We need to find $S(s)$

Estimating $S(s)$

—

$$G_1(s) = G_J(s)S(s) \tag{16}$$

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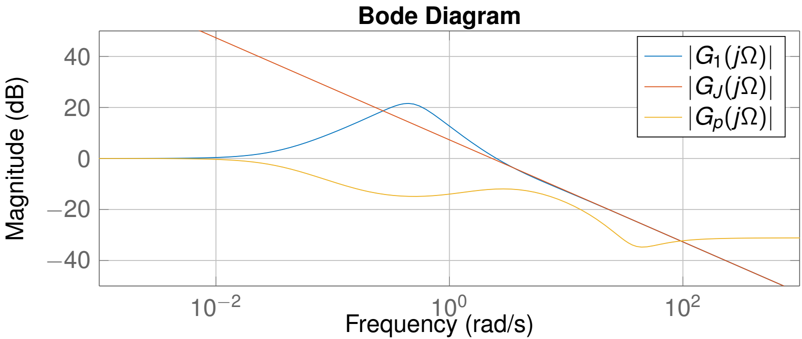
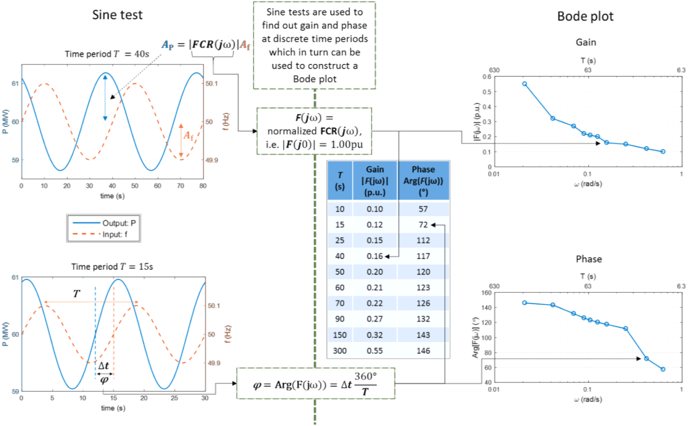
— Need to estimate H

Estimating H



Dataset from Statkraft

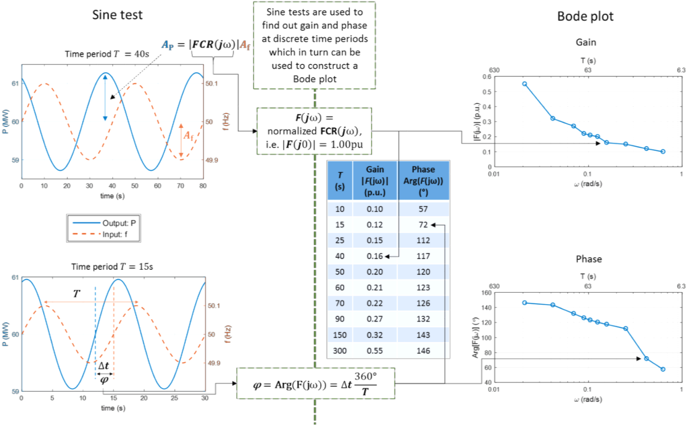
— One of Norway's biggest power producers.



T (s)	Gain $\lvert F(j\omega)\rvert$ (p.u.)	Phase Arg($F(j\omega)$) (°)
10	0.10	57
15	0.12	72
25	0.15	112
40	0.16	117
50	0.20	120
60	0.21	123
70	0.22	126
90	0.27	132
150	0.32	143
300	0.55	146

Dataset from Statkraft

- One of Norway’s biggest power producers.
- They performed the tests from the draft requirements



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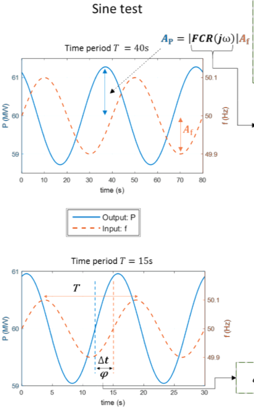
Dataset from Statkraft

- One of Norway's biggest power producers.
- They performed the tests from the draft requirements
- By chance I had PMU measurements from the same plant.



Sine tests are used to find out gain and phase at discrete time periods which in turn can be used to construct a Bode plot

$F(j\omega)$ = normalized $\mathbf{FCR}(j\omega)$, i.e. $|F(j0)| = 1.00$pu

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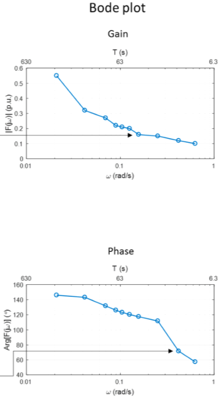
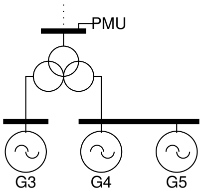
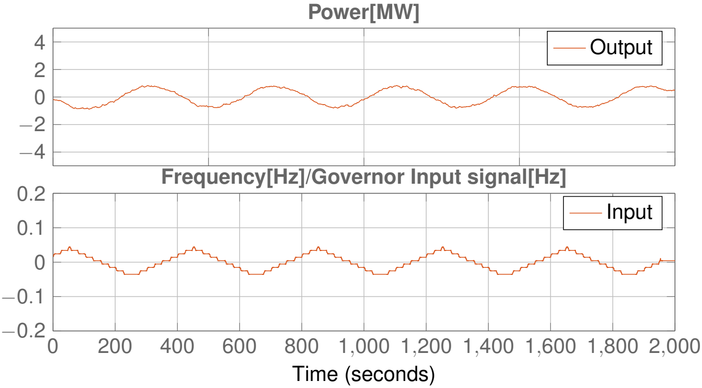
$$\varphi = \mathrm{Arg}(F(j\omega)) = \Delta t \frac{360°}{T}$$



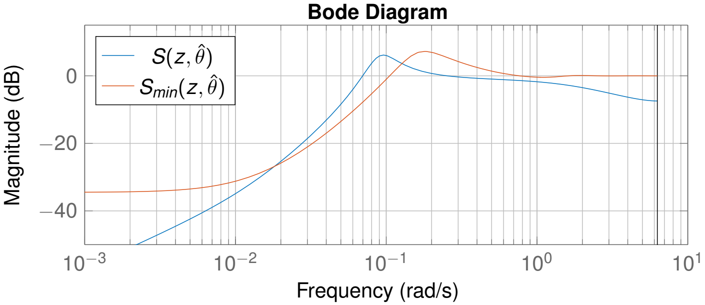
Single line diagram of the plant



Datasets used



Estimated sensitivity functions



Estimated $G_1(s)$