Vector fitting for estimation of turbine governor parameters

Sigurd Hofsmo Jakobsen

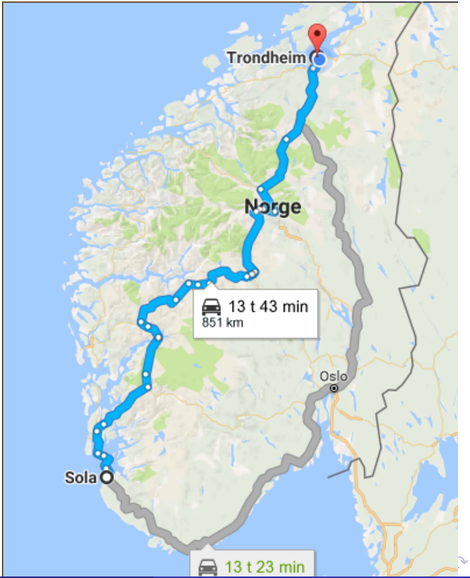
Department of electric power engineering

April 20, 2017

Outline

Very short bio

- From Sola



Very short bio

- From Sola
- Studied and works in Trondheim

Very short bio

- From Sola
- Studied and works in Trondheim
- Worked as a research engineer from 2013-2015 for SINTEF Energy Research

Very short bio

- From Sola
- Studied and works in Trondheim
- Worked as a research engineer from 2013-2015 for SINTEF Energy Research
- Currently PhD student at NTNU

Very short bio

- From Sola
- Studied and works in Trondheim
- Worked as a research engineer from 2013-2015 for SINTEF Energy Research
- Currently PhD student at NTNU
- 10% position at SINTEF Energy Research

Outline

Projects I contribute to

- FP7 project GARPUR

Projects I contribute to

- FP7 project GARPUR
- FP7 project ELECTRA

Projects I contribute to

- FP7 project GARPUR
- FP7 project ELECTRA
- NRC HILP

Projects I contribute to

- FP7 project GARPUR
- FP7 project ELECTRA
- NRC HILP

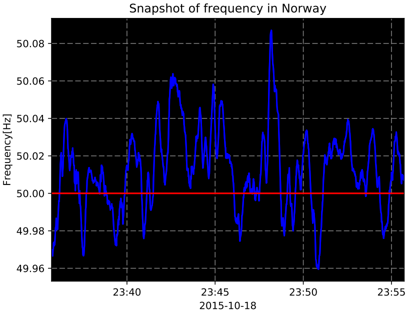
Projects I contribute to

- FP7 project GARPUR
- FP7 project ELECTRA
- NRC HILP
- NRC FASAD

Outline

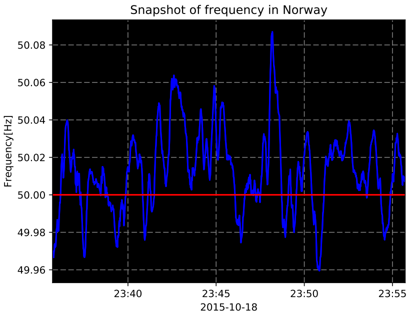
Frequency quality

- There are concerns about the frequency quality in the Nordic countries



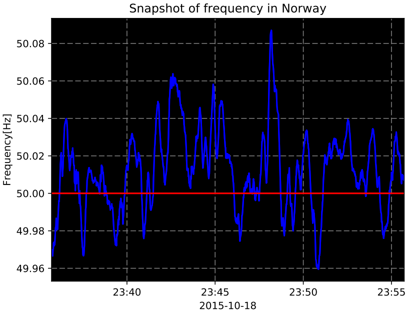
Frequency quality

- There are concerns about the frequency quality in the Nordic countries
- To prevent large deviations in frequency generators participate in frequency containment control (FCC)



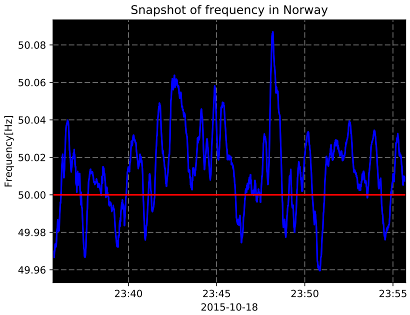
Frequency quality

- There are concerns about the frequency quality in the Nordic countries
- To prevent large deviations in frequency generators participate in frequency containment control (FCC)
- FCC is sometimes referred to as primary control



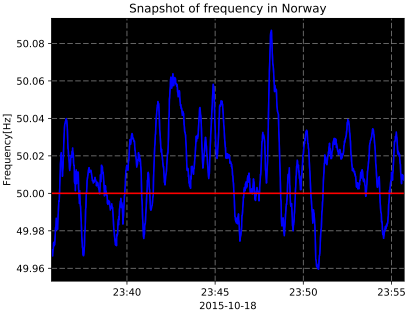
Frequency quality

- There are concerns about the frequency quality in the Nordic countries
- To prevent large deviations in frequency generators participate in frequency containment control (FCC)
- FCC is sometimes referred to as primary control
- Generators of a certain size have to contribute to this control



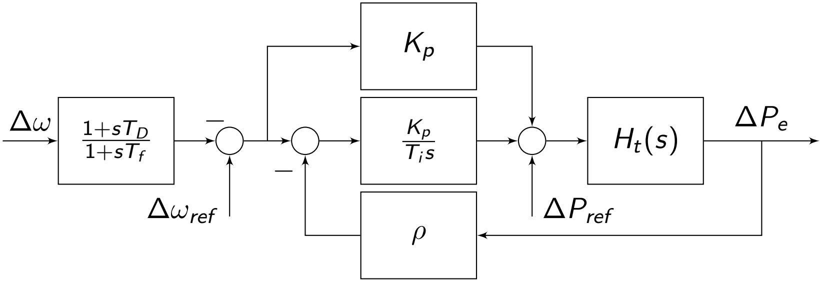
Frequency quality

- There are concerns about the frequency quality in the Nordic countries
- To prevent large deviations in frequency generators participate in frequency containment control (FCC)
- FCC is sometimes referred to as primary control
- Generators of a certain size have to contribute to this control
- FCC greatly influences the frequency quality



Hydro turbine governors

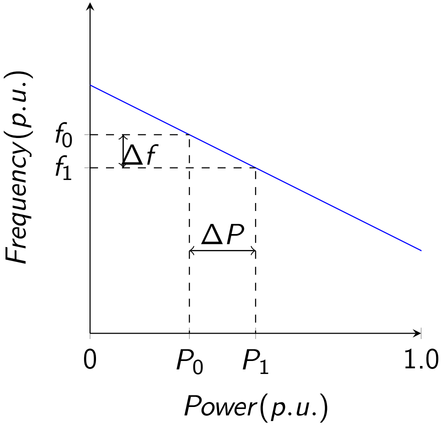
- Typically implemented as a PID controller



$$H = -K_p \frac{1+sT_D}{1+sT_f} \cdot \frac{1+sT_i}{\rho K_p + sT_i} \quad (1)$$

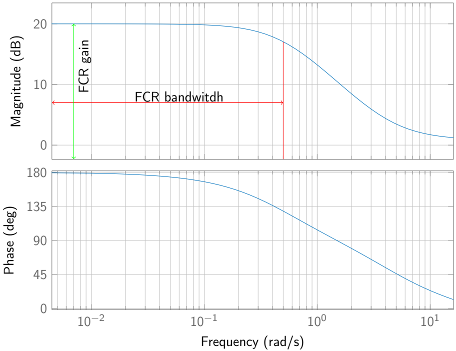
Hydro turbine governors

- By identifying a model of the governor we can:
  - Say something about its static performance



Hydro turbine governors

- By identifying a model of the governor we can:
  - Say something about its static performance
  - Say something about its dynamic performance



Previous work

- The ARX[1] model structure was used on parts of the same dataset as used in this study in [1]
- The authors of [2] use constrained optimization on disturbance data from the Crete power system.
- The authors of [3] apply an unscented Kalman filter to the measurements from a trip event in the Midcontinent Independent System.
- Field measurements for a more detailed identification is used in [4]
- Other studies using only simulation data also exist.

[1] Autoregressive exogenous

Outline

Vector fitting basics

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

$$Y(s) = H(s) \cdot U(s) \qquad (2)$$

Vector fitting basics

- Vector fitting fits a transfer function to measured input and output data
- Finding the parameters in (3) is a nonlinear optimization.

$$Y(s) = H(s) \cdot U(s) \tag{2}$$

$$H(s) = d + \sum_{i=1}^{n_p} \frac{r_i}{s - p_i} \tag{3}$$

Vector fitting basics

- Vector fitting fits a transfer function to measured input and output data
- Finding the parameters in (3) is a nonlinear optimization.
- The idea behind vector fitting presented in [5] is to formulate the augmented problem (4) with known poles $\tilde{p}_i$.

$$Y(s) = H(s) \cdot U(s) \qquad (2)$$

$$H(s) = d + \sum_{i=1}^{n_p} \frac{r_i}{s - p_i} \qquad (3)$$

$$\sigma(s)H(s) = d + \sum_{i=1}^{n_p} \frac{r_i}{s - \tilde{p}_i} \qquad (4)$$

Vector fitting basics continued

- How do we choose $\sigma(s)$?

Vector fitting basics continued

- How do we choose $\sigma(s)$?
- First rewrite (3) and (4).

$$H(s) = \frac{\prod_{i=1}^{n_z}(1 - z_i)}{\prod_{i=1}^{n_p}(1 - p_i)} \tag{5}$$

$$\sigma(s)H(s) = \frac{\prod_{i=1}^{n_z}(1 - z_i)}{\prod_{i=1}^{n_p}(1 - \tilde{p}_i)} \tag{6}$$

Vector fitting basics continued

- How do we choose $\sigma(s)$?
- First rewrite (3) and (4).
- We can see that the zeros of $\sigma(s)$ must cancel the poles of (5)

$$H(s) = \frac{\prod_{i=1}^{n_z}(1 - z_i)}{\prod_{i=1}^{n_p}(1 - p_i)} \tag{5}$$

$$\sigma(s)H(s) = \frac{\prod_{i=1}^{n_z}(1 - z_i)}{\prod_{i=1}^{n_p}(1 - \tilde{p}_i)} \tag{6}$$

$$\sigma(s) = \frac{\prod_{i=1}^{n_z}(1 - \tilde{z}_i)}{\prod_{i=1}^{n_p}(1 - \tilde{p}_i)} \tag{7}$$

Vector fitting basics continued

- (4) can now be solved by measuring $H(s)$ at multiple frequencies and multiplying with (5) which gives (6)

$$H(s) = d + \sum_{i=1}^{n_p} \frac{r_i}{s - p_i} \tag{3}$$

$$\sigma(s)H(s) = d + \sum_{i=1}^{n_p} \frac{r_i}{s - \tilde{p}_i} \tag{4}$$

$$\sigma(s) = 1 + \sum_{i=1}^{n_p} \frac{k_i}{s - \tilde{p}_i} \tag{5}$$

$$d + \sum_{i=1}^{n_p} \frac{r_i}{s - \tilde{p}_i} = (1 + \sum_{i=1}^{n_p} \frac{k_i}{s - \tilde{p}_i})H_{measured}(s) \tag{6}$$

Vector fitting basics continued

- (4) can now be solved by measuring $H(s)$ at multiple frequencies and multiplying with (5) which gives (6)
- In (6) the unknowns are d, r_i, k_i for $\tilde{p}_i$ an initial guess is used.

$$H(s) = d + \sum_{i=1}^{n_p} \frac{r_i}{s - p_i} \tag{3}$$

$$\sigma(s)H(s) = d + \sum_{i=1}^{n_p} \frac{r_i}{s - \tilde{p}_i} \tag{4}$$

$$\sigma(s) = 1 + \sum_{i=1}^{n_p} \frac{k_i}{s - \tilde{p}_i} \tag{5}$$

$$d + \sum_{i=1}^{n_p} \frac{r_i}{s - \tilde{p}_i} = (1 + \sum_{i=1}^{n_p} \frac{k_i}{s - \tilde{p}_i})H_{measured}(s) \tag{6}$$

Vector fitting basics continued

- (4) can now be solved by measuring $H(s)$ at multiple frequencies and multiplying with (5) which gives (6)
- In (6) the unknowns are d, r_i, k_i for $\tilde{p}_i$ an initial guess is used.
- The procedure is performed again with the calculated zeros of (4) as the updated starting poles $\tilde{p}_i$

$$H(s) = d + \sum_{i=1}^{n_p} \frac{r_i}{s - p_i} \tag{3}$$

$$\sigma(s)H(s) = d + \sum_{i=1}^{n_p} \frac{r_i}{s - \tilde{p}_i} \tag{4}$$

$$\sigma(s) = 1 + \sum_{i=1}^{n_p} \frac{k_i}{s - \tilde{p}_i} \tag{5}$$

$$d + \sum_{i=1}^{n_p} \frac{r_i}{s - \tilde{p}_i} = (1 + \sum_{i=1}^{n_p} \frac{k_i}{s - \tilde{p}_i})H_{measured}(s) \tag{6}$$

Convergence criteria for vector fitting

- Multiple convergence criteria exist and are discussed in [6].

Convergence criteria for vector fitting

- Multiple convergence criteria exist and are discussed in [6].
- One of them uses the fact that if all k_i are zero (6) has converged to (3)

$$H(s) = d + \sum_{i=1}^{n_p} \frac{r_i}{s - p_i} \tag{3}$$

$$d + \sum_{i=1}^{n_p} \frac{r_i}{s - \tilde{p}_i} = (1 + \sum_{i=1}^{n_p} \frac{k_i}{s - \tilde{p}_i}) H_{measured}(s) \tag{6}$$

Convergence criteria for vector fitting

- Multiple convergence criteria exist and are discussed in [6].
- One of them uses the fact that if all k_i are zero (6) has converged to (3)

$$H(s) = d + \sum_{i=1}^{n_p} \frac{r_i}{s - p_i} \tag{3}$$

$$d + \sum_{i=1}^{n_p} \frac{r_i}{s - \tilde{p}_i} = (1 + \sum_{i=1}^{n_p} \frac{k_i}{s - \tilde{p}_i}) H_{measured}(s) \tag{6}$$

- Mathematically the criterion is formulated as follows.

$$\| \frac{\tilde{k}_1}{\tilde{p}_1}, \cdots, \frac{\tilde{k}_{n_p}}{\tilde{p}_{n_p}} \| < \epsilon \tag{7}$$

Method for model order reduction

- The order of the obtained models are reduced by discarding residues according to:

$$|\frac{r_i}{p_i},| < \epsilon, i \in n_p \tag{8}$$

Vector fitting in the time domain

- Multiplying the augmented problem (4) by the input and performing Laplace inverse gives vector fitting in the time domain [7]:

$$y(t) \approx \tilde{d}x(t) + \sum_{i=1}^{n_p} \tilde{r}_i x_i - \sum_{i=1}^{n_p} \tilde{k}_i y_i \tag{9}$$

Vector fitting in the time domain

- Multiplying the augmented problem (4) by the input and performing Laplace inverse gives vector fitting in the time domain [7]:

$$y(t) \approx \tilde{d}x(t) + \sum_{i=1}^{n_p} \tilde{r}_i x_i - \sum_{i=1}^{n_p} \tilde{k}_i y_i \tag{9}$$

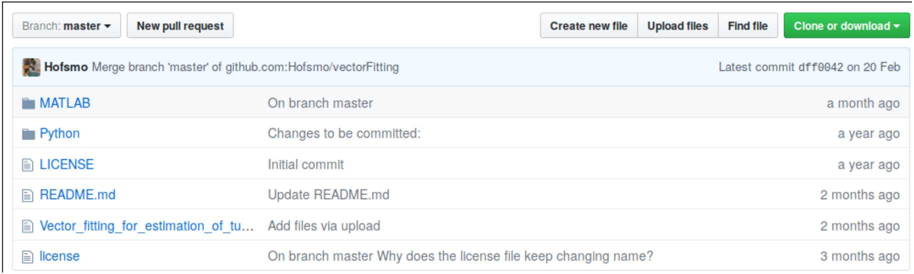
- In (9) x_i and y_i are the solutions of convolution integrals solved numerically using the trapezoidal rule:

$$x_i = \int_0^t e^{\tilde{p}_i(t-\tau)} x_i(\tau) d\tau \tag{10}$$

$$y_i = \int_0^t e^{\tilde{p}_i(t-\tau)} y_i(\tau) d\tau \tag{11}$$

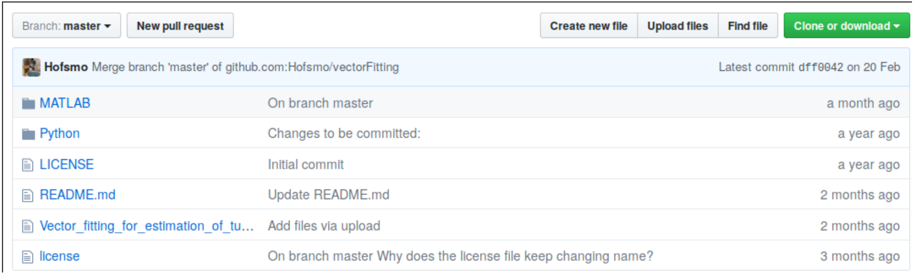
Code for vector fitting

- The vector fitting implementation used in this work is available on GitHub: `https://github.com/Hofsmo/vectorFitting`



Code for vector fitting

- The vector fitting implementation used in this work is available on GitHub: `https://github.com/Hofsmo/vectorFitting`
- The original vector fitting implementation in the frequency domain is available on `https://www.sintef.no/projectweb/vectfit/`



Outline

Detailing of research questions

The method was designed such that the following questions could be answered regarding:

1. Is configuration easy?

Detailing of research questions

The method was designed such that the following questions could be answered regarding:

1. Is configuration easy?
2. Are the results valid outside of the measurement time window?

Detailing of research questions

The method was designed such that the following questions could be answered regarding:

1. Is configuration easy?
2. Are the results valid outside of the measurement time window?
3. Can the results be obtained using a small measurement time window?

Detailing of research questions

The method was designed such that the following questions could be answered regarding:

1. Is configuration easy?
2. Are the results valid outside of the measurement time window?
3. Can the results be obtained using a small measurement time window?
4. Is the method fast?

Steps in the identification method

1. Data collection

Steps in the identification method

1. Data collection
2. Partitioning of data

Steps in the identification method

1. Data collection
2. Partitioning of data
3. Preprocessing of data

Steps in the identification method

1. Data collection
2. Partitioning of data
3. Preprocessing of data
4. Vector fitting on all data partitions

Steps in the identification method

1. Data collection
2. Partitioning of data
3. Preprocessing of data
4. Vector fitting on all data partitions
5. Cross validation and model selection

Data collection

- Real PMU[2] measurements from the Norwegian system

[2] Phasor measurement unit (PMU)

Data collection

- Real PMU[2] measurements from the Norwegian system
- Six generators at two different locations.

[2] Phasor measurement unit (PMU)

Data collection

- Real PMU[2] measurements from the Norwegian system
- Six generators at two different locations.
- The data sets are one hour long and the sampling frequency was $50\,Hz$.

[2] Phasor measurement unit (PMU)

Data collection

- Real PMU[2] measurements from the Norwegian system
- Six generators at two different locations.
- The data sets are one hour long and the sampling frequency was $50 Hz$.
- Data sets with obvious nonlinearities such as ramping and saturation were discarded.

[2] Phasor measurement unit (PMU)

Preprocessing of data

- All data were decimated with a factor of 50.

Preprocessing of data

- All data were decimated with a factor of 50.
- The average was removed from all datasets.

Preprocessing of data

- All data were decimated with a factor of 50.
- The average was removed from all datasets.
- The data was run through an antialiasing filter.

Cross validation and model selection

- No signal selection method was developed.

Cross validation and model selection

- No signal selection method was developed.
- Instead all possible cross validations were attempted.

Cross validation and model selection

- No signal selection method was developed.
- Instead all possible cross validations were attempted.
- For a partition with length five minutes that adds up to 132 possibilities for cross validation.

Cross validation and model selection

- No signal selection method was developed.
- Instead all possible cross validations were attempted.
- For a partition with length five minutes that adds up to 132 possibilities for cross validation.
- Self validation was not allowed.

Outline

Choice of starting poles

- Starting poles should be chosen in the frequency range of interest.

Minutes	Poles	[0, 0.5]	[0, 0.1]	[0, 0.05]
5	Real	66.66%	66.66%	66.66%
	Complex	73.07%	74.60%	73.53%
	Mixed	74.89%	74.69%	74.42%
10	Real	68.45%	68.45%	68.45%
	Complex	72.49%	73.84%	72.75%
	Mixed	73.49%	72.60%	73.73%
15	Real	66.01%	66.01%	66.01%
	Complex	69.72%	70.40%	70.33%
	Mixed	70.86%	70.43%	70.12%
20	Real	70.73%	70.73%	70.73%
	Complex	72.53%	72.27%	71.16%
	Mixed	71.28%	71.91%	72.38%
25	Real	60.27%	60.27%	60.27%
	Complex	63.45%	62.31%	63.45%
	Mixed	63.14%	63.45%	63.45%
30	Real	68.01%	68.01%	68.01%
	Complex	71.75%	71.45%	72.54%
	Mixed	72.52%	71.44%	72.21%

Choice of starting poles

- Starting poles should be chosen in the frequency range of interest.
- They can be:
  - purely real
  - purely complex
  - or a combination

Minutes	Poles	$[0, 0.5]$	$[0, 0.1]$	$[0, 0.05]$
5	Real	66.66%	66.66%	66.66%
	Complex	73.07%	74.60%	73.53%
	Mixed	74.89%	74.69%	74.42%
10	Real	68.45%	68.45%	68.45%
	Complex	72.49%	73.84%	72.75%
	Mixed	73.49%	72.60%	73.73%
15	Real	66.01%	66.01%	66.01%
	Complex	69.72%	70.40%	70.33%
	Mixed	70.86%	70.43%	70.12%
20	Real	70.73%	70.73%	70.73%
	Complex	72.53%	72.27%	71.16%
	Mixed	71.28%	71.91%	72.38%
25	Real	60.27%	60.27%	60.27%
	Complex	63.45%	62.31%	63.45%
	Mixed	63.14%	63.45%	63.45%
30	Real	68.01%	68.01%	68.01%
	Complex	71.75%	71.45%	72.54%
	Mixed	72.52%	71.44%	72.21%

Choice of starting poles

- Starting poles should be chosen in the frequency range of interest.
- They can be:
    - purely real
    - purely complex
    - or a combination
- The poles were linearly spaced from zero up until the end of the interval.

Minutes	Poles	$[0, 0.5]$	$[0, 0.1]$	$[0, 0.05]$
5	Real	66.66%	66.66%	66.66%
	Complex	73.07%	74.60%	73.53%
	Mixed	74.89%	74.69%	74.42%
10	Real	68.45%	68.45%	68.45%
	Complex	72.49%	73.84%	72.75%
	Mixed	73.49%	72.60%	73.73%
15	Real	66.01%	66.01%	66.01%
	Complex	69.72%	70.40%	70.33%
	Mixed	70.86%	70.43%	70.12%
20	Real	70.73%	70.73%	70.73%
	Complex	72.53%	72.27%	71.16%
	Mixed	71.28%	71.91%	72.38%
25	Real	60.27%	60.27%	60.27%
	Complex	63.45%	62.31%	63.45%
	Mixed	63.14%	63.45%	63.45%
30	Real	68.01%	68.01%	68.01%
	Complex	71.75%	71.45%	72.54%
	Mixed	72.52%	71.44%	72.21%

Choice of starting poles

- Starting poles should be chosen in the frequency range of interest.
- They can be:
  - purely real
  - purely complex
  - or a combination
- The poles were linearly spaced from zero up until the end of the interval.
- Purely complex starting poles performs more or less the same as mixed poles.

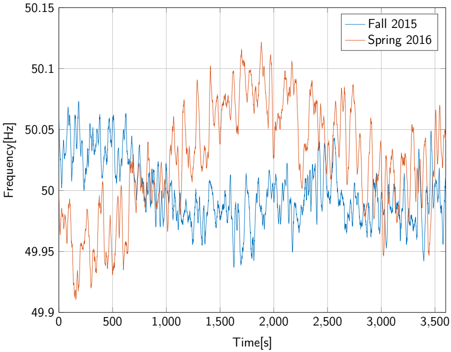
Minutes	Poles	$[0, 0.5]$	$[0, 0.1]$	$[0, 0.05]$
5	Real	66.66%	66.66%	66.66%
	Complex	73.07%	74.60%	73.53%
	Mixed	74.89%	74.69%	74.42%
10	Real	68.45%	68.45%	68.45%
	Complex	72.49%	73.84%	72.75%
	Mixed	73.49%	72.60%	73.73%
15	Real	66.01%	66.01%	66.01%
	Complex	69.72%	70.40%	70.33%
	Mixed	70.86%	70.43%	70.12%
20	Real	70.73%	70.73%	70.73%
	Complex	72.53%	72.27%	71.16%
	Mixed	71.28%	71.91%	72.38%
25	Real	60.27%	60.27%	60.27%
	Complex	63.45%	62.31%	63.45%
	Mixed	63.14%	63.45%	63.45%
30	Real	68.01%	68.01%	68.01%
	Complex	71.75%	71.45%	72.54%
	Mixed	72.52%	71.44%	72.21%

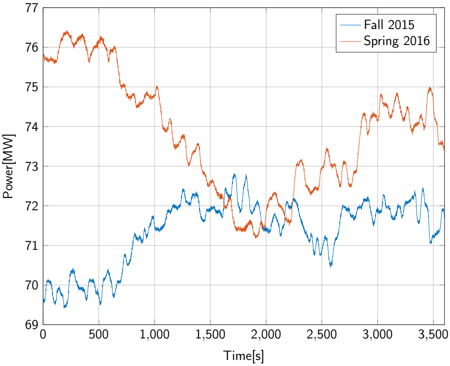
Choice of starting poles

- Starting poles should be chosen in the frequency range of interest.
- They can be:
  - purely real
  - purely complex
  - or a combination
- The poles were linearly spaced from zero up until the end of the interval.
- Purely complex starting poles performs more or less the same as mixed poles.
- There is little difference between the length of the time windows.

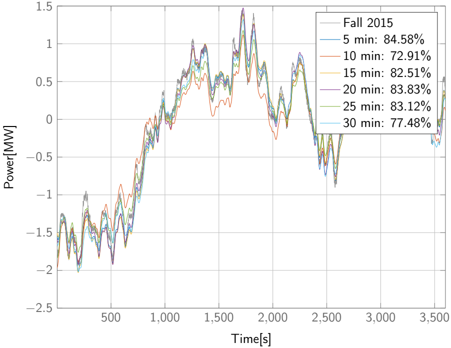
Minutes	Poles	[0, 0.5]	[0, 0.1]	[0, 0.05]
5	Real	66.66%	66.66%	66.66%
	Complex	73.07%	74.60%	73.53%
	Mixed	74.89%	74.69%	74.42%
10	Real	68.45%	68.45%	68.45%
	Complex	72.49%	73.84%	72.75%
	Mixed	73.49%	72.60%	73.73%
15	Real	66.01%	66.01%	66.01%
	Complex	69.72%	70.40%	70.33%
	Mixed	70.86%	70.43%	70.12%
20	Real	70.73%	70.73%	70.73%
	Complex	72.53%	72.27%	71.16%
	Mixed	71.28%	71.91%	72.38%
25	Real	60.27%	60.27%	60.27%
	Complex	63.45%	62.31%	63.45%
	Mixed	63.14%	63.45%	63.45%
30	Real	68.01%	68.01%	68.01%
	Complex	71.75%	71.45%	72.54%
	Mixed	72.52%	71.44%	72.21%

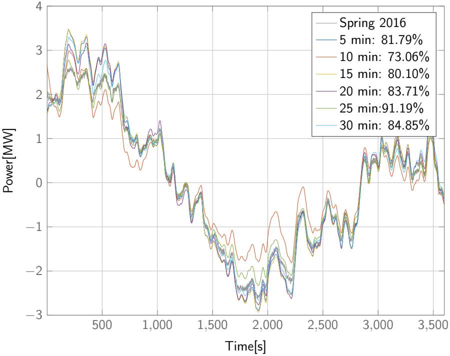
Cross validation using distant data sets



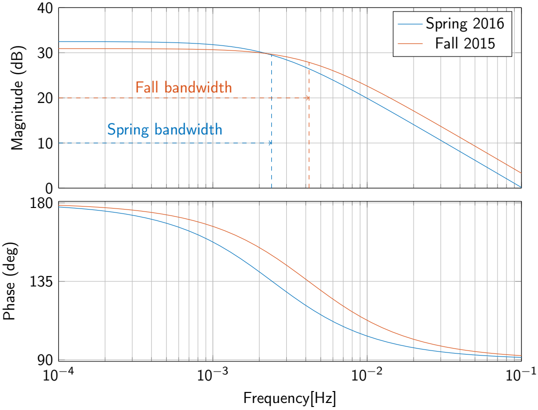


Cross validation using distant data sets





Estimated droop and bandwidth



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

Outline

Conclusions

- Vector fitting obtains good fit normally in the range between 70% and 90%.

Conclusions

- Vector fitting obtains good fit normally in the range between 70% and 90%.
- It is fast with an execution time around $0.1s$

Conclusions

- Vector fitting obtains good fit normally in the range between 70% and 90%.
- It is fast with an execution time around $0.1s$
- It is robust, just filter your data and choose poles in the frequency range of interest and it works.

Conclusions

- Vector fitting obtains good fit normally in the range between 70% and 90%.
- It is fast with an execution time around $0.1s$
- It is robust, just filter your data and choose poles in the frequency range of interest and it works.
- Good results were obtained with time windows as short as five minutes.

Conclusions

- Vector fitting obtains good fit normally in the range between 70% and 90%.
- It is fast with an execution time around $0.1s$
- It is robust, just filter your data and choose poles in the frequency range of interest and it works.
- Good results were obtained with time windows as short as five minutes.
- One drawback is the lack of uncertainty quantification for identified parameters

Outline

References I

[1] Dinh Thuc Duong, Kjetil Uhlen, Stig Løvlund, and Erik Alexander Jansson, "Estimation of hydro turbine-governor's transfer function from PMU measurements," , presented at the IEEE PES General Meeting, Boston: IEEE, Jul. 2016.

[2] N. D. Hatziargyriou, E. S. Karapidakis, G. S. Stavrakakis, I. F. Dimopoulos, and K. Kalaitzakis, "Identification of synchronous machine parameters using constrained optimization," in *Power Tech Proceedings, 2001 IEEE Porto*, vol. 4, 2001, 5 pp. vol.4–. DOI: 10.1109/PTC.2001.964812.

References II

[3] H. G. Aghamolki, Z. Miao, L. Fan, W. Jiang, and D. Manjure, "Identification of synchronous generator model with frequency control using unscented kalman filter," *Electric Power Systems Research*, vol. 126, pp. 45–55, Sep. 2015, ISSN: 0378-7796. DOI: 10.1016/j.epsr.2015.04.016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0378779615001224 (visited on 01/18/2016).

[4] L. Saarinen, P. Norrlund, and U. Lundin, "Field measurements and system identification of three frequency controlling hydropower plants," *IEEE Transactions on Energy Conversion*, vol. 30, no. 3, pp. 1061–1068, Sep. 2015, ISSN: 0885-8969. DOI: 10.1109/TEC.2015.2425915.

References III

[5] B. Gustavsen and A. Semlyen, "Rational approximation of frequency domain responses by vector fitting," *IEEE Transactions on Power Delivery*, vol. 14, no. 3, pp. 1052–1061, Jul. 1999, ISSN: 0885-8977. DOI: 10.1109/61.772353.

[6] Stefano Grivet-Talocia and Bjørn Gustavsen, *Passive macromodeling theory and applications*, ser. Wiley Series in Microwave and Optical Enineering. John Wiley & Sons, 2016, ISBN: 978-1-118-09491-4.

[7] S. Grivet-Talocia, "Package macromodeling via time-domain vector fitting," *IEEE Microwave and Wireless Components Letters*, vol. 13, no. 11, pp. 472–474, Nov. 2003, ISSN: 1531-1309. DOI: 10.1109/LMWC.2003.819378.