Vector fitting for estimation of turbine governing system parameters

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***Abstract*—With the introduction of more and more renewables into the power system both the inertia and the primary frequency reserves are expected to decrease. It is therefore a growing concern that the frequency quality will deteriorate. One way of mitigating these problems may be a more detailed monitoring of the generators providing the primary reserves.**

A promising approach for monitoring the generators is to identify turbine governing system parameters using system identification. This will allow for estimating the droop and the bandwidth of the governor, parameters that are important for the primary control. Furthermore, if this can be reliably done on ambient data, updated estimates of these parameters can be obtained relatively fast.

In this paper we will look into how vector fitting can be used for this purpose. The algorithm possesses some interesting properties for automatically constructing models from ambient data. How this can be done will be presented together with results obtained using real data from the Norwegian power system. A simple criterion for reducing the obtained model order is also proposed.

***Keywords*—Turbine governors, PMUs, ambient data, system identification, time domain, vector fitting**

I. Hydro governor parameter estimation using vector fitting

The introduction of more and more renewables into the power system has lead to a concern for the system's frequency, since these units often do not provide inertia or the ability to provide frequency containment reserves (FCR). To mitigate these problems for continental Europe one proposal is to use hydro power plants in the Nordic, as providers of FCR thorough interconnectors. For the Nordic countries this is both an opportunity and a challenge as their systems will have to both handle their own intermittent production and large shifts in power flows on interconnectors to continental Europe. These challenges are well understood by the Nordic transmission system operators (TSOs) and are thoroughly covered in their challenges and opportunities report [1].

In this paper we will investigate the possibility to use phasor measurement units (PMUs) to monitor the FCR. One advantage of this approach is that TSOs can use their own equipment to monitor generators, which are important power system equipment not owned by the generators. Furthermore, we propose to use ambient PMU data to not disturb the operation of the power plant. This will serve as a supplement to the required data exchange between generators and TSOs and can also be used on generators not covered by the grid code on requirement for grid connection of generators (RfG)[2].

System identification techniques have previously been applied to real system data in papers such as [3]–[5]. The authors of [5] use constrained optimization on disturbance data from the Crete power system and the authors of [4] apply an unscented Kalman filter to the measurements from a trip event in the Midcontinent Independent System. Common for these papers is the use of data from disturbances. For the purpose of model validation this is sufficient, however, for a more continuous monitoring one would need to use data from normal system operation. An example on how this can be achieved is presented in [3] where an auto regressive exogenous (ARX) model structure is applied to recordings from normal system operation in the Norwegian grid.

One disadvantage of the ARX model structure is that one needs to select an appropriate model order to get a good fit. For the purpose of performing a continuous monitoring it would be an advantage if less tuning was needed. One method that may have these properties is time domain vector fitting [6]. Therefore, we will in this paper present how this method can be applied to estimate model of turbine governors. Furthermore, we will show that the method does indeed possess interesting properties for online applications, due to its performance with respect to speed, accuracy and the amount of tuning needed.

Time domain vector fitting is presented in section II and the code used is available at [7]. Hydro governors are discussed in section III and the results are presented and discussed in section IV. The final section covers the conclusion regarding the methods performance and how it should be tuned.

II. Time domain vector fitting

Vector fitting was introduced for the frequency domain in [8] and later extended to the time domain in [6]. It is an iterative algorithm where each step start with a set of starting poles that are updated at the end of the step until convergence is reached.

A. The algorithm

In the vector fitting algorithm it is assumed that the transfer function of the system can be expressed using the rational transfer function:

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

In (1) the unknowns to be estimated are d, r_i and p_i. Since some of the unknowns are situated in the denominator the problem is not linear. To make the problem linear it is multiplied by an unknown scaling function $\sigma(s)$ with known poles $\tilde{p}_i$ defined such that:

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

It can be proven that the zeros of $\sigma(s)$ will be equal to the poles of (1) [9]. $\sigma(s)$ is unknown, hence the following approximation for $\sigma(s)$ given in [8] is introduced as:

$$\sigma(s) \approx 1 + \sum_{i=1}^{n_p} \frac{k_i}{s - \tilde{p}_i} = \frac{\prod_{i=1}^{n_z}(1 - \tilde{z}_i)}{\prod_{i=1}^{n_p}(1 - \tilde{p}_i)} \tag{3}$$

Notice that if the zeros $\tilde{z}_i$ of (3) equal the starting poles $\tilde{p}_i$ (3), the weighted problem (2) equals the original problem (1). This implies that if the correct poles of the system is identified, k_i equals zero.

Vector fitting in the time domain can now be obtained by multiplying (2) by the input signal $u(t)$ and performing laplace inverse.

$$y(t) \approx \tilde{d}x(t) + \sum_{i=1}^{n_p} \tilde{r}_i x_i - \sum_{i=1}^{n_p} \tilde{k}_i y_i \tag{4}$$

Notice that the unknowns in (4) are denoted with a ˜ to mark that these are recalculated every iteration. The waveforms $x_i(t)$ and $y_i(t)$ are obtained from the following convolution integrals:

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

$$y_i = \int_0^t e^{\tilde{p}_i(t-\tau)} y_i(\tau) d\tau \tag{6}$$

These integrals can be solved using an IIR filter [6].

$$x_i[k] = \alpha_i x_i[k-1] + \beta x[k] + \beta x[k-1] \tag{7}$$

In (7) we use the coefficients defined in [10], which implements the trapezoidal method for numerical integration.

$$\alpha = \frac{1 + \tilde{p}_i \frac{\Delta t}{2}}{1 - \tilde{p}_i \frac{\Delta t}{2}}, \beta = \frac{\Delta t}{2 - \tilde{p}_i \Delta t} \tag{8}$$

where Δt is the sampling time.

The unknowns of (4) are now obtained using least square fitting. Then the updated poles to be used in the next iteration of the vector fitting is obtained as the zeros of (3).

B. Starting poles for vector fitting

Unlike the (autoregressive moving average exogenous) ARMAX type model structures, vector fitting does not require one to find an appropriate model order for the system. One only needs to define a set of starting poles, which should be given according to the rule of thumbs described in [8] that is the starting poles should be:

- Linearly or logarithmically spaced
- Real or complex conjugate

Real poles should only be used to fit smooth functions, whereas complex conjugate poles should be chosen in the general case. Furthermore, for complex conjugate starting poles the real part should be $1/100$ of the complex part.

When it comes to the order of the model [8] states that the starting poles that converge towards poles that are not in the system one tries to fit will have low values of the corresponding residues. This fact is used to make an automatic order reduction procedure. The procedure is inspired by the following convergence criterion from [9]:

$$\|\frac{\tilde{k}_1}{\tilde{p}_1}, \cdots, \frac{\tilde{k}_{n_p}}{\tilde{p}_{n_p}}\| < \epsilon \tag{9}$$

which states that the vector norm of the normalized residues of $\sigma(s)$ should be below a certain tolerance limit ϵ. A similar criterion can also be stated for the residues of the function we are fitting, that is:

$$|\frac{r_i}{p_i}, | < \epsilon, i \in n_p \tag{10}$$

where the normalized residue below the tolerance limit ϵ are discarded. Other model reduction schemes have been proposed in [11] where single value decomposition (SVD) and balanced realization model is compared.

C. Indicator for goodness of fit

Various indicators exist for measuring the goodness of fit when performing system identification. Typically theses indicators try to give an indication on which model performs best with respect to both ability to predict and complexity. In this paper, however, we will use the simple indicator normalised root mean square error (NRMSE) as defined in (11) from [12].

$$\text{NRMSE} = 100(1 - \frac{||y - \hat{y}||}{||y - \bar{y}||}) \tag{11}$$

where y is the measured response and $\hat{y}$ is the estimated response. The reason is that it is intuitively easy to understand. Furthermore, as will be shown later, vector fitting normally provides low order models meaning that the penalty term for higher order models, included in most other indicators, becomes less relevant. For an introduction to indicators on goodness of fit please refer to a standard text book in system identification such as [13].

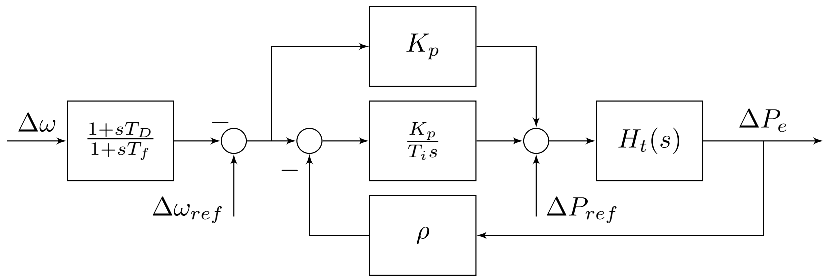


Fig. 1: PID hydro turbine governor

TABLE I: Hydro turbine governor parameters

Variable	Explanation	Approximate value
T_D	Derivative time	$1-2s$
T_f	Low pass filter time constant	$0.2s$
K_p	Controller gain	$1-3$
T_i	Integral time	$2-10s$
ρ	Droop	$0.04-0.12$

III. Hydro turbine governors

Since the Norwegian system is dominated by hydro units our study will only consider hydro units. Therefore, a few basic properties of hydro governors useful for understanding identification of these will be briefly covered.

A. Transfer function of hydro turbine governors

In Fig. 1 a simple block system representation of a governor and a turbine is depicted. The turbine and generator are represented by the transfer function $H_t(s)$, and their dynamics are assumed to be negligible in the frequency range under study. Unlike [14] the derivative action of the governor is moved before the frequency reference to prevent changes in the frequency reference to influence the derivative. The parameters in the model are presented in Table I.

As explained in section II the vector fitting algorithm requires a set of starting poles. To get an indication on what range to choose from, the transfer function of the governor can be analyzed.

$$H = -K_p \frac{1+sT_D}{1+sT_f} \cdot \frac{1+sT_i}{\rho K_p + sT_i} \tag{12}$$

From (12) one can see that the system's poles will be placed at:

$$p_1 = -\frac{1}{T_f},\ p_2 = -\frac{\rho K_p}{T_i} \tag{13}$$

This means that it is possible to get purely real poles or one complex conjugate pair. Using the parameter values from Table I one can see that the maximum range of the poles will be $5Hz$ and $0.18Hz$.

B. Potential problems when performing the fitting

In our approach we will try to identify the transfer function of the governor by measuring the frequency and the power at a generator busbar. As can be seen from Fig. 1 the results may be influenced by changes in the frequency and power reference set points. The power reference is typically changed as a ramp around the hour change. Unless the ramp is known an identification during such an event will risk identifying the ramp, instead of the governor dynamics. One also has to be careful to select a filter that filters out electromechanical dynamics. Furthermore both the governor and turbine contain nonlinearities such as dead bands and limiters [14]. However, in this paper it is assumed that the governor behaves linearly around the operating point where its behaviour is observed. Furthermore, when working with ambient data it is important to choose a measurement time window where the relevant dynamics of the governor is excited.

IV. Vector fitting on real system PMU data

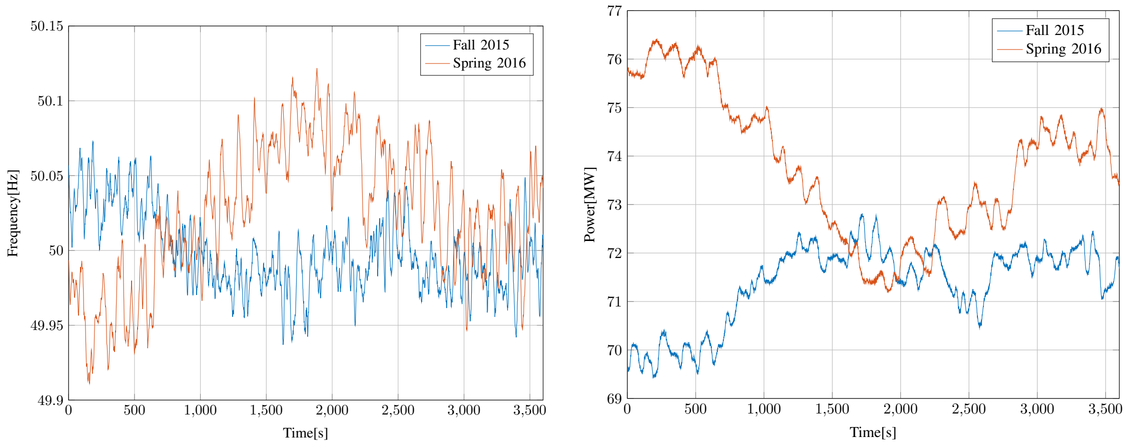
To test the applicability of vector fitting on real data, PMU measurements from five generators at two different location in Norway were collected. When testing vector fitting for online identification there are some properties we want to look for:

1) Easy configuration.
2) Results valid outside of the measurement window.
3) A small measurement time window.
4) Low execution time

A. Identification approach

The approach used for performing the identification consists of five main steps:

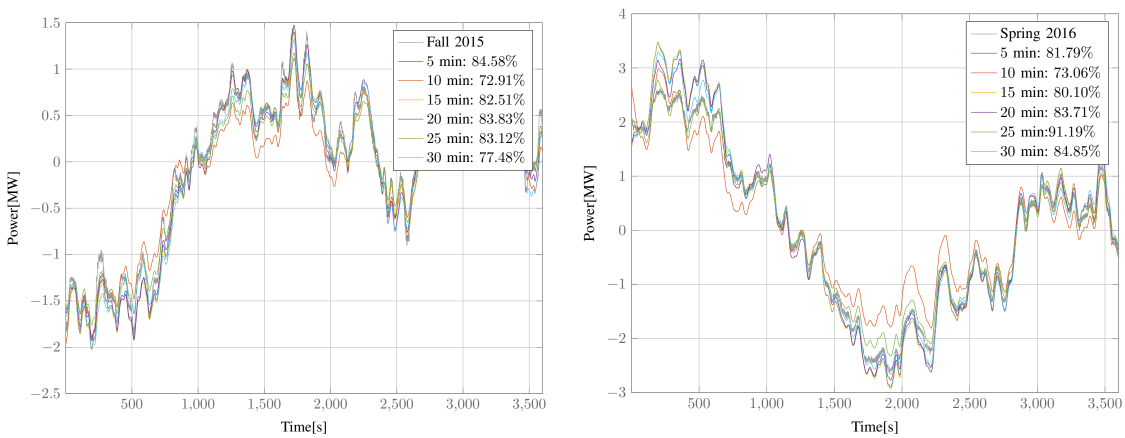
1) Data collection: This step consists of collecting PMU data measurements from locations in the Norwegian grid.
2) Partitioning of data set: When performing identification It is important to ensure that a good fit is obtained. To do this it is normal to partition the data set into one identification part and one validation part, an approach referred to as cross validation [13]. In principle cross validation could be done by merely splitting the data set into two parts. However, due to nonlinearities, lack of dynamics or ramping, parts of a data sets may be unfit for either identification or validation. To circumvent this problem each data set is partitioned into partitions of equal lengths. For a data set of one hour and partitions of five minutes this gives 132 cross validation possibilities.
3) Preprocessing of data: All data is detrended, decimated and filtered through a low pass filter. The decimation



(a) Frequency of datasets

(b) Power output of datasets

Fig. 2: Datasets for fall 2015 and spring 2016



(a) Validating the constructed models against the fall dataset

(b) Validating the constructed models against the spring dataset

Fig. 3: Validation of models constructed from spring and fall dataset

factor and filter cut-off frequency is chosen such that dynamics up to $0.5Hz$ can be captured. At this frequency one may have electromechanical dynamics, however, it is unlikely that dynamic that close to the Nyquist frequency will be identified.

4) Vector fitting is performed on all partitions
5) Cross validation and model selection All cross validation possibilities are attempted and the model with the highest NRMSE is selected.

B. *Starting order for vector fitting*

As explained in section II the vector fitting algorithm takes a set of starting poles as input. It is therefore of interest to investigate which starting orders are best for performing vector fitting on hydro governor data. To test this 19 data sets with a measurement time window of 60 minutes were selected.

To decide what ranges of starting poles to test it is useful to further investigate how many poles one can expect to find and what values they will take. From the sampling rate of the processed signal a natural upper bound of 0.5 is easy to deduce using the Nyquist criterion. Furthermore, if one considers the results obtained from (13) and the values from Table I one can see that the maximum value of a pole should be no more than $0.18Hz$. However, when testing different starting poles we will try up to $0.5Hz$ which is the maximum we can identify.

To find the best starting poles for hydro governor fitting different combinations of both real starting poles, complex conjugate starting poles and combinations were tested for the ranges reported in Table II. The purely real and purely complex starting poles were linearly spaced and consisted of ten starting poles. The mixed starting poles were a superposition of the purely real and purely complex. Furthermore, different time windows were also tested.

From Table II it is evident that best fits are obtained when the starting poles contains complex conjugate pairs. When it comes to the distribution of the poles there are no significant difference. It is therefore reasonable to choose the maximum starting pole as half of the sampling frequency. The important

TABLE II: Fit for the different starting poles and 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%

decision then reduces to which cut-off frequency to use in the antialiasing filter.

C. Measurement time window

Preferably one would want to obtain a good fit with a time window as short as possible. Furthermore, one would want the results to be valid for a wide as possible time range. In subsection IV-B we investigated the best starting poles for different time windows and as can be seen from Table II good *NRMSE* values were obtained for all time windows. This should not be very surprising as we look at dynamics in the minute time range, which means that a time window of a couple of minutes should be enough. It is also of interest to investigate the validity range of a constructed model in terms of time. To do this we will cross validate models constructed from datasets that are measured half a year apart. The datasets are from one measurement site and are from fall 2015 and spring 2016 and are depicted in Fig. 2.

In Fig. 3 the result of using the frequency signal from the spring dataset as input to the fall model and vice versa is depicted. From this one can see that models constructed half a year apart from the validation data perform satisfactory. It should also be noted that all time windows perform well, however, it varies which one is the best. The reason for this is that the fit is more dependent on the dynamics contained in the signal than the length of the signal.

Another aspect relevant for choosing the time window is the execution time. Since, the execution time increases with the number of samples a too large time window may result in a too long execution time. However, with a time window of half an hour one identification takes approximately half a second, which should for all practical purposes be fast enough. It is also worth noticing that the maximum model order obtained using vector fitting and the proposed model reduction scheme is third order models.

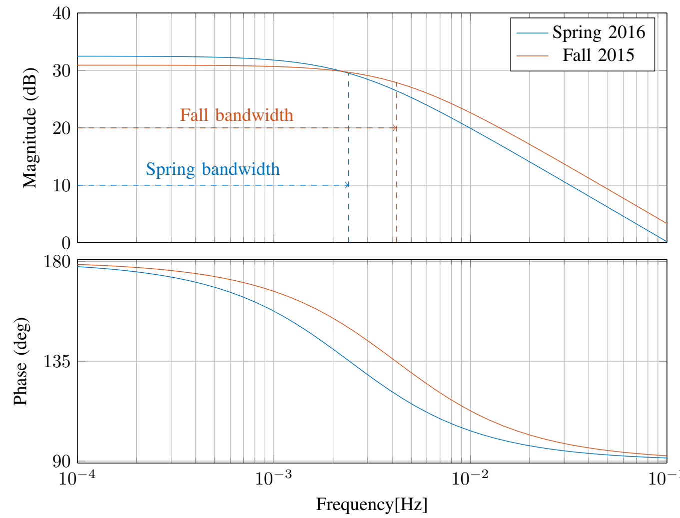


Fig. 4: Bode plot showing governor gain and bandwidth

TABLE III: Estimated droop for generator at two different times

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

D. Applications

The most obvious application for identifying governor models are system validation. As one can see from Fig. 3 the identified models represent the real system behaviour well and can be used for this purpose. Another useful application is the ability to estimate the droop and bandwidth of the turbine governor. This can be used to check whether or not generator droop settings are close to their reported values or to validate that generators actually change their droop when instructed.

In Fig. 4 the Bode plots of the transfer functions constructed from five minute time windows using the data sets presented in Fig. 2 are presented. From the bode plot one can see both the available bandwidth as well as the droop. Bode plots are useful for graphical presenting the dynamics of the transfer functions. However, one is also quite likely to be interested in the values of the droop and the bandwidth. These values are reported in Table III. An interesting observation is that the estimated values of the droop and the bandwidth differ in between the fall and spring dataset. This observation rises an important question, that is out of the scope of this paper. Namely, is the deviation due to an actual change in the droop settings or due to uncertainties in the estimation technique.

V. CONCLUSIONS

Vector fitting shows very promising results for identifying governor parameters obtaining good fits for all the considered datasets. The most notable feature being the ability to obtain good fits with little tuning. In short the tuning decisions that has to be made are:

1) The cut off-frequency of the antialiasing filter

2) The time window

To choose the time window the decisive factor should be the dynamics contained in the signal a discussion not covered in this paper.

The algorithm also obtains the results quickly and the proposed model reduction scheme results in low order models.

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REFERENCES

[1] Statnett, Fingrid, Energinet.DK, and Svenska Kraftnt. (2016). Challenges and opportunities report, [Online]. Available: http://www.statnett.no/Global/Dokumenter/Challenges%20and%20opportunities_Report.pdf (visited on 08/30/2016).

[2] European Commission. (Apr. 14, 2016). Network code on requirements for grid connection applicable to all generators, [Online]. Available: http://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:32016R0631&from=EN (visited on 09/01/2016).

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

[4] 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).

[5] 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.

[6] 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.

[7] S. H. Jakobsen. (2016). Hofsmo/vectorFitting, GitHub, [Online]. Available: https://github.com/Hofsmo/vectorFitting (visited on 04/21/2016).

[8] 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.

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

[10] A. Ubolli and B. Gustavsen, "Applicability of time domain and z-domain vector fitting to rational modeling from time domain responses with consideration to circuit solver integration method," in *2010 IEEE 14th Workshop on Signal Propagation on Interconnects (SPI)*, May 2010, pp. 69–72. DOI: 10.1109/SPI.2010.5483573.

[11] A. Ramirez, "Vector fitting-based calculation of frequency-dependent network equivalents by frequency partitioning and model-order reduction," *IEEE Transactions on Power Delivery*, vol. 24, no. 1, pp. 410–415, Jan. 2009, ISSN: 0885-8977. DOI: 10.1109/TPWRD.2008.921139.

[12] MATLAB. (2016). Loss function and model quality metrics - MATLAB & simulink - MathWorks nordic, [Online]. Available: http://se.mathworks.com/help/ident/ug/model-quality-metrics.html (visited on 04/28/2016).

[13] L. Ljung, *System identification*. Springer, 1998. [Online]. Available: http://link.springer.com/chapter/10.1007/978-1-4612-1768-8_11 (visited on 03/29/2016).

[14] Working Group on Prime Mover and Energy Supply Models for System Dynamic Performance Studies, "Hydraulic turbine and turbine control models for system dynamic studies," *IEEE Transactions on Power Systems*, vol. 7, no. 1, pp. 167–179, Feb. 1992, bibtex: ieee_wg_1992, ISSN: 0885-8950. DOI: 10.1109/59.141700.