Identification of hydro turbine governors using PMU data

Sigurd Hofsmo Jakobsen, Kjetil Uhlen
Department of Electric Power Engineering
Norwegian University of Science and Technology,
Trondheim, Norway,
sigurd.h.jakobsen@ntnu.no

Xavier Bombois
Laboratoire Ampère UMR CNRS 5005
Ecole Centrale de Lyon,
Ecully, France

***Abstract*—Recent concerns for the frequency quality in the Nordic power system has lead to an increased interest in hydro turbine governors. Among this research have been papers on identification of turbine and turbine governor dynamics from PMU measurements. However, no attempt at a theoretical validation has been made. This paper fills in this gap by a theoretical validation using a DC power flow model for modelling the power flows in the grids. By doing this it is shown that it is indeed possible to identify the closed loop transfer function of the turbine, turbine governor and electromechanical dynamics. An experimental validation using results from a real life power system are also presented.**

I. INTRODUCTION

Recent concerns for the frequency quality in the Nordic power system [1] have lead to an increased interest in the dynamic performance of hydro turbine governors. Among the research being carried out is identification of turbine governors using local measurements from phasor measurement units (PMUs). The added value for the TSOs is the possibility to validate the performance of the governors using their own measurements instead of relying on information from the production plant owners.

In this article the aim is to test the hypothesis that turbine governor dynamics can be identified using PMU measurements at generator bus bars. In the literature one can already find papers where identification methods have been applied to PMU measurements for the identification of turbine dynamics [2]–[6]. In [2] an unscented Kalman filter is used to identify both turbine and electromechanical dynamics using data from a generator trip event. Another paper using data from disturbance[1] recordings is [4] who uses constrained optimization to perform the identification. Other papers such as [3], [5], [6] use data from normal operation to do the identification. This is of particular interest since the system is not always subjected to large disturbances. We will therefore focus on measurements from normal operation in this paper. The papers [3], [6] uses the ARX and ARMAX model structure to perform the identification whereas [5] uses time domain vector fitting. In the present paper the same dataset as in [3], [5] will be used for the experimental validation.

[1]In this context disturbance refers to a larger power system event, i.e. load or generation tripping and not normal load variations

What lacks in the previous papers is an explicit study on how the input and output to the identification is related to each other through the power system. In other words there is no analysis of whether or not the proposed methods will yield consistent results. In this paper we give conditions under which a consistent estimate of the transfer function between the electrical power and the speed of a generator can be deduced using only PMU data from normal operation.

The structure of the paper will be as follows. The system under study is presented in Section II, the theoretical validation in Section III, simulation results are give in Section IV, results from a real life power system is given in Section V, and finally the conclusions in Section VI.

II. TEST SYSTEM FOR IDENTIFICATION

To be able to analyze the identifiability of turbine and turbine governors the components influencing the input and output signals to the identification has to be modeled. To do this we will consider a turbine located at bus 1 in a power system. The location will be denoted by adding the number 1 to the subscript for the considered signals and functions. In Fig. 1 the model used for representing a hydro turbine governor and the turbine used in this paper is presented. For the model of the turbine we have chosen a linearised model represented by a first order transfer function with a time constant T_w. Physically this time constant represents the time the water uses to flow from the reservoir to the turbine at the operating point of the linearization. The governor is a PID regulator with a droop feedback ρ, which uses the generator speed $\Delta\omega_1(s)$ to modify the power output $\Delta P_{m1}(s)$ of the turbine. The transfer function between $\Delta\omega_1(s)$ and $\Delta P_{m1}(s)$ will be denoted $G_{t1}(s)$:

$$\Delta P_{m1}(s) = G_{t1}(s)\Delta\omega_1(s) \tag{1}$$

It is worth noting that the steady state gain of $G_{t1}(s)$ is always equal to the inverse of the droop $1/\rho$. The power output is changed by adjusting the guide vane opening $\Delta g_1(s)$. Other modelling choices are available and a reference for many common choices are [7].

To identify $G_{t1}(s)$, one would need to use a data set with $\Delta\omega_1(s)$ as input and $\Delta P_{m1}(s)$ as output. Unfortunately, $\Delta P_{m1}(s)$ is not available to the TSOs. Instead, they can install

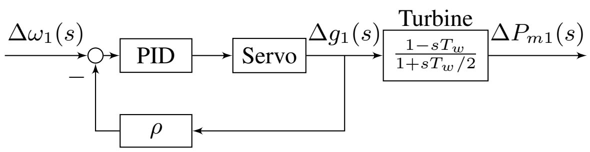

Fig. 1: Hydro turbine governor and turbine $G_{t1}(s)$

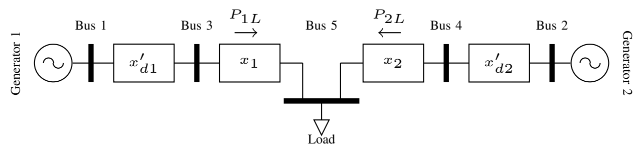

Fig. 2: Single line diagram of the system

PMUs at the bus bar where the generator is connected to their system. This will allow them to measure the electrical power and frequency at the bus bar. The relation between the electrical power, mechanical power, and generator speed is given by the swing equation:

$$\Delta\omega_1(s) = \frac{\Delta P_{m1}(s) - \Delta P_{e1}(s)}{2\mathcal{H}_1 s + K_{d1}} \tag{2}$$

where:

$\mathcal{H}_1$**:** is the inertia constant of the machine, which is the inertia of the machine scaled according to its rating.

K_{d1}**:** is the damping constant.

From now on we will denote $G_{J1}(s) = 1/(2\mathcal{H}_1 s + K_{d1})$. We will also combine (1) and (2) to obtain:

$$\Delta\omega_1(s) = -\frac{G_{J1}(s)}{1 + G_{J1}(s)G_{t1}(s)}\Delta P_{e1}(s) + v_1(s) \tag{3}$$

where $v_1(s)$ is an additional contribution representing the process disturbance acting on generator 1. It will be modeled as white noise $e_1(s)^2$ filtered by the transfer function $H_1(s)$. One should take note of that $H_1(s)$ can also be a closed loop transfer function.

Consequently, using measurements of $\Delta\omega_1(s)$ and $\Delta P_{e1}(s)$ we will never be able to identify $G_{t1}(s)$. If we can identify a transfer function based on these data it will be the closed-loop transfer function $G_1(s) = -G_{J1}(s)/(1+G_{t1}(s)G_{J1}(s))$. It should be noted that the steady state gain of $G_1(s)$ is approximately equal to the droop ρ, which means that we will still be able to deduce information on the turbine governor's droop settings.

What remains to be proven is whether or not $G_1(s)$ can be consistently identified from normal operation data. For this purpose it is important to analyze how $\Delta P_{e1}(s)$ is generated in the power system. We will therefore introduce the simple power system depicted in Fig 2. The system consists of two power plant buses, one load bus and the lines connecting them. As already mentioned, our objective is to identify $G_1(s)$ for the power plant at bus 1. The power plant at bus 2 is an aggregated plant designed to represent the rest of the production capacity in the network and the load at bus 5 is meant to represent all loads in the system. In the power system there is a strong coupling between active power and frequency. Due to this we will assume that reactive power and voltages can be assumed constant for our analysis, allowing us to model the flow on the lines using a dc power flow. This design choice allows us to include the most relevant dynamics in our analysis, while keeping the system small.

[2]This is abuse of notation since white noise has no Laplace transform.

In Fig. 2 there are four reactances, x_1 and x_2 are line reactances, and x'_{d1} and x'_{d2} are the subtransient reactances of the generators at bus 1 and bus 2 respectively. It is important to notice that the subtransient reactances are internal to the generators. Therefore, our PMU measurements used for identifying $G_1(s)$ will be taken at bus 3 not bus 1. We have already assumed a dc power flow, hence the electrical power measured at bus 3 will be the same as for bus 1. Furthermore, we will also assume the frequency measured at bus 3 $\Delta f_3(s)$ is a good estimate of the electric speed at bus 1, in other words $\omega_1(s) \approx 2\pi f_3(s)$.

For the load it is assumed that the load has a frequency dependency given by the transfer function $G_l(s)$, this is commonly due to rotating loads. The frequency at the load is estimated using the centre of inertia equation.

$$f_5(s) = 2\pi\frac{\sum_{i=1}^{2}\omega_i(s)\mathcal{H}_i}{\sum_{i=1}^{2}\mathcal{H}_i} \tag{4}$$

In addition to frequency dependent part the load consists of a stochastic part $v_5(s) = H_5(s)e_5(s)$, which represents the load changes due to random load switching. It is modeled as white noise $e_5(s)$ filtered by the filter $H_5(s)$.

The dc power flow assumption allows us to establish the following relationship between the electrical angle at the two production plant buses and the active power at the load bus [8].

$$\mathbf{P}_e = \begin{bmatrix}\mathbf{Y}_{11} - \mathbf{Y}_{12}\mathbf{Y}_{22}^{-1}\mathbf{Y}_{21} & \mathbf{Y}_{12}\mathbf{Y}_{22}^{-1}\end{bmatrix}\begin{bmatrix}\theta_e \\ \mathbf{P}_l\end{bmatrix} \tag{5}$$

where the $\mathbf{Y}_{ij}$ are submatrices of the nodal admittance matrix, θ_e is vector of generator angles, $\mathbf{P}_e$ is the vector of generator bus active powers, and $\mathbf{P}_l$ is the vector of load active powers. We can now derive a linear relationship between the plants and load. This linear relationship is presented in Fig. 3 where the K factors are constants derived from (4) and (5).

In Fig. 3 the process noise acting on the power plants are depicted and we see that the second power plant like power plant 1 is perturbed by filtered white noise $v_2(s) = H_2(s)e_2(s)$. An important assumption is that the noise terms $v_1(s)$, $v_2(s)$, and $v_5(s)$ are all statistically uncorrelated. This assumption should easily hold for $v_5(s)$ as consumers are unlikely to change their consumption due to process noise at production plants. It is also very unlikely that the process noises at power plants situated at geographical distant locations are dependent on each other.

Based on Fig. 3 one can deduce, that in normal operation, $\Delta P_{e1}(s)$ is made of a contribution of the two process noises $v_1(s) = H_1(s)e_1(s)$ and $v_2(s) = H_2(s)e_2(s)$ as well as the

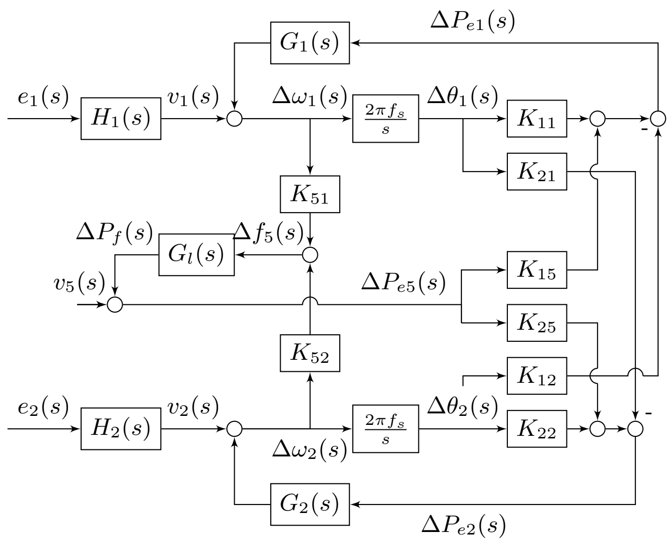

Fig. 3: Block diagram of the system depicted in Fig. 2

random load changes $v_5(s) = H_5(s)e_5(s)$. We can now write $P_{e1}(s)$ as a function of the white noises.

$$\Delta P_{e1}(s) = T_5(s)e_5(s) + T_1(s)e_1(s) + T_2(s)e_2(s) \quad (6)$$

where $T_5(s)$, $T_1(s)$ and $T_2(s)$ are stable transfer functions. The contribution of $e_2(s)$ and $e_5(s)$ are important, indeed, these contributions show that $\Delta P_{e1}(s)$ will be made up of external signals even under normal operations. These external signals will excite the dynamics of $G_1(s)$ and help in the identification. Opposed to this $e_1(s)$ could be detrimental as it introduces a correlation between $\Delta P_{e1}(s)$ and the process disturbance $v_1(s)$. However, we will show that this correlation will not lead to identification problems if a certain technical condition is satisfied.

III. Theoretical validation

For the validation we suppose that, after the application of an antialiasing filter, we have collected N samples of $\Delta P_{e1}(t)$ and $\Delta\omega_1(t)$ with a certain sampling frequency. We will denote these samples $u[n]$ and $y[n]$ respectively, where $[n]$ denotes discrete time. These sampled signals make up the dataset $Z^N = \{u[n], y[n] | n = 1 \dots N\}$, and they are assumed related by:

$$\mathcal{S} : y[n] = G_1(z, \theta_0)u[n] + H_1(z, \theta_0)e_1[n] \quad (7)$$

where $G_1(z, \theta_0)$ and $H_1(z, \theta_0)$ are discrete versions of the transfer functions $G_1(s)$ and $H_1(s)$, $H_1(z, \theta_0)$ is assumed monic, $e_1[n]$ is discrete time white noise, θ_0 is the vector that parametrize the true system $\mathcal{S}$, and z^{-1} is the delay operator.

For the input signal $u[n]$ we have that:

$$u[n] = T_5(z)e_5[n] + T_1(z)e_1[n] + T_2(z)e_2[n] \quad (8)$$

where $T_5(z)$, $T_1(z)$, and $T_2(z)$ are discrete versions of the transfer functions in (6). We also define $\sigma_{e_1}^2$, $\sigma_{e_2}^2$, and $\sigma_{e_5}^2$ as the power spectra of $e_1[n]$, $e_2[n]$, and $e_5[n]$.[3]

Before moving on to the proof what we mean by identification should be defined. It is simply that given the dataset Z^N and a full order model structure $\mathcal{M} = \{G_1(z, \theta), H_1(z, \theta)\}$ we can deduce an estimate of the unknown parameter vector $\hat{\theta}_N$ using prediction identification [9]:

$$\hat{\theta}_N = \arg\min_{\theta} \frac{1}{N} \sum_{n=1}^{N} \epsilon^2(n, \theta) \quad (9)$$

with:

$$\epsilon(n, \theta) = H_1^{-1}(z, \theta)(y[n] - G_1(z, \theta)u[n]) \quad (10)$$

In order to validate our identification setting it is important to verify whether or not (9)-(10) will lead to a consistent estimate of θ_0 when the input signal is given by (8), or in other words, whether or not (8) is a sufficiently informative signal for the identification of $\mathcal{S}$. For $\hat{\theta}_N$ to be a consistent estimate, one needs to verify that the true parameter vector θ_0 is the unique solution to the asymptotic prediction criterion:

$$\theta^* = \arg\min_{\theta} \bar{E}\epsilon^2(n, \theta) \quad (11)$$

with

$$\bar{E}\epsilon^2(n, \theta) = \lim_{N\to\infty} \frac{1}{N} \sum_{t=1}^{N} E\epsilon^2(n, \theta) \quad (12)$$

The operator E denotes the expectation operator.

Theorem 1. *Consider the dataset $Z^N = \{u[n], y[n] | n = 1 \dots N\}$ where Z^N is generated by* (7) *and* (8)*. Suppose also that $e_1[n]$, $e_2[n]$, and $e_5[n]$ are independent white noises. Then the prediction error criterion* (9)-(10) *yields a consistent estimate of θ_0 if there is a delay in either $G_1(z, \theta_0)$ or $T_1(z)$.*

Proof. We start by writing the prediction error in terms of the input at node *1* by inserting (7) into (10) to get.

$$\epsilon[n, \theta] = e_1[n] + \frac{\Delta H_1(z, \theta)}{H_1(z, \theta)} e_1[n] + \frac{\Delta G_1(z, \theta)}{H_1(z, \theta)} u[n] \quad (13)$$

with $\Delta H_1(z, \theta) = H_1(z, \theta_0) - H_1(z, \theta)$ and $\Delta G_1(z, \theta) = G_1(z, \theta_0) - G_1(z, \theta)$. By inserting (8) into (13) we can write $\epsilon[n, \theta]$ as:

$$\begin{aligned} \epsilon[n, \theta] = {} & e_1[n] + \nu(z, \theta)e_1[n] \\ & + \Gamma_2(z, \theta)e_2[n] + \Gamma_5(z, \theta)e_5[n] \end{aligned} \quad (14)$$

with:

$$\nu(z, \theta) = \frac{\Delta H_1(z, \theta) + \Delta G_1(z, \theta)T_1(z)}{H_1(z, \theta)} \quad (15)$$

and

$$\Gamma_{m\in 2,5}(z, \theta) = \frac{\Delta G_1(z, \theta)}{H_1(z, \theta)} T_{m\in 2,5}(z) \quad (16)$$

Due to the fact that $H_1(z)$ is monic and the fact that $\Delta G_1(z, \theta)T_1(z)$ contains a delay, we conclude that when

[3]For a white noise process the spectrum is its variance.

non zero $\nu(z,\theta)$ also contains a delay. This property and the assumption on the independence of $e_1[n]$, $e_2[n]$, and $e_5[n]$ can be used to write $\bar{E}\epsilon^2(n,\theta)$ as:

$$\begin{aligned}\bar{E}\epsilon^2[n,\theta] = \sigma_{e_1}^2 \\ &+ \frac{1}{2\pi}\int_{-\pi}^{\pi}\nu(e^{j\omega},\theta)\sigma_{e_1}^2\nu^*(e^{j\omega},\theta)d\omega \\ &+ \frac{1}{2\pi}\int_{-\pi}^{\pi}\Gamma_2(e^{j\omega},\theta)\sigma_{e_2}^2\Gamma_2^*(e^{j\omega},\theta)d\omega \\ &+ \frac{1}{2\pi}\int_{-\pi}^{\pi}\Gamma_5(e^{j\omega},\theta)\sigma_{e_5}^2\Gamma_5^*(e^{j\omega},\theta)d\omega\end{aligned} \tag{17}$$

To prove the consistency, we will show that θ_0 is the unique minimizer of (17), that is it is the unique parameter vector θ^* yielding $\bar{E}\epsilon^2[n,\theta^*] = \sigma_{e_1}^2$. We observe that this only holds if $\nu(z,\theta^*) = \Gamma_2(z,\theta^*) = \Gamma_5(z,\theta^*) = 0$. From (15) and (16) we see that the latter statement implies that $\Delta G_1(z,\theta^*) = \Delta H_1(z,\theta^*) = 0$. This again implies $\theta^* = \theta_0$. □

IV. Simulation Results

In this section validation of the identification of turbine dynamics using a simulation model developed in Simulink will be presented. The system is depicted in Fig. 2 and was presented in Section II. It was tuned to give a response similar to the one area system in [10].

To obtain the models a Box-Jenkins model structure was assumed, which has the following structure:

$$y(t) = \frac{B(z)}{F(z)}u(t) + \frac{C(z)}{D(z)}e(t) \tag{18}$$

The reason for this choice is that it is a general model structure that allows for modelling the denominator dynamics of $G_1(z,\theta_0)$ and $H_1(z,\theta_0)$ separately. The model order used was $[4,6,6,5,0]$ where the model orders are given in alphabetical order and the last number represents the time delay. The simulated signals were given with a sampling frequency of $50Hz$ to be the same as for a PMU signal. In addition the signals were decimated using a factor of 25. The system identification toolbox developed for MATLAB was used for the filtering and identification [11].

It should be noted that the order of the delay is chosen to be zero. This means that if there is a delay in $G_1(z,\theta_0)$ it is shorter than $0.5s$. If one considers the condition stated in 1 one realizes that this implies that there has to be a delay longer than $0.5s$ in $T_1(z)$.

To validate the results we first start by plotting the analytical transfer function of the true system against an estimated one. This is depicted in Fig. 4, where one can see that there is an almost perfect match between $G_1(s)$ and $G_1(z,\hat{\theta}_N)$. One can also observe how the identified function follows the dynamics of the inverse of $G_{t1}(s)$ for low frequencies. Although, in Fig. 4 one can also see that the transfer function starts deviating from the governor as the frequency raises, one can still extract information on the steady state gain of the transfer function. This implies that one can derive information

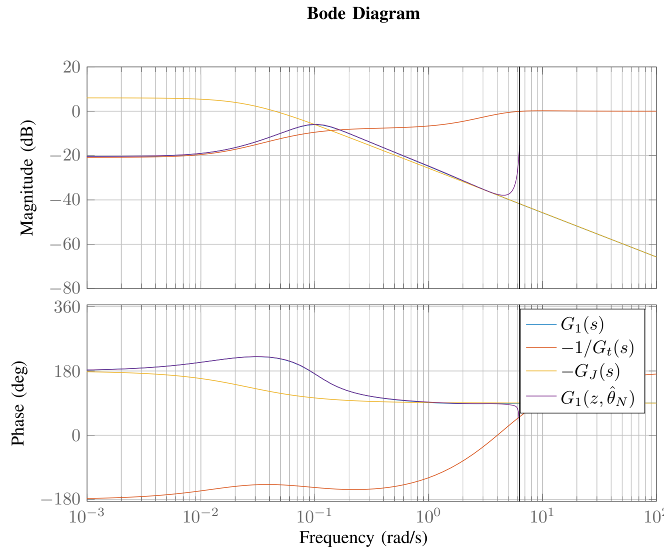

Fig. 4: Bode plots of actual transfer functions and identified transfer function using simulation data

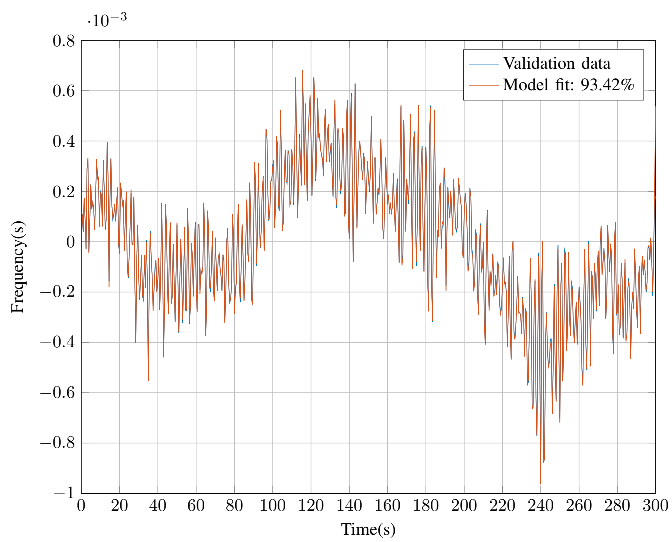

Fig. 5: Comparison of actual and identified transfer function subjected to a signal using simulation data

on the steady state gain of $G_{t1}(s)$, which is related to the droop settings, from the measurements. In general it will be difficult to say something about the bandwidth of the governor since the dynamics will be a mix of the electromechanical and governor dynamics, however, one will still be able to say something about the plants response as a whole.

A common method for benchmarking the performance of identified transfer functions is to measure a second data set $Z_v = \{u_v[n], y_v[n] | n = 1 \ldots N_v\}$. We then apply $u_v[n]$ to the identified model $G_1(z,\hat{\theta}_N)$ to obtain a signal $\hat{y}[n]$ that is:

$$\hat{y}[n] = G_1(z,\hat{\theta})u_v[n] \tag{19}$$

$\hat{y}[n]$ can then be plotted against $y_v[n]$ to allow for a visualization of the identified model's performance. In addition one

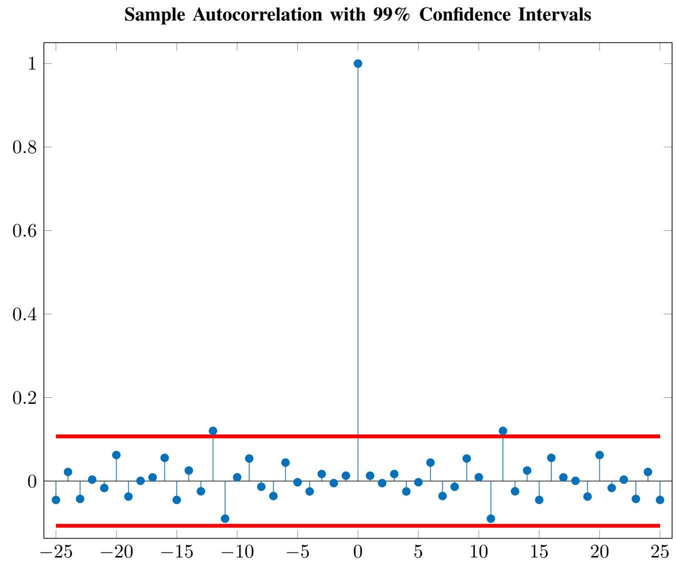

Fig. 6: Residuals for identified model using simulation data

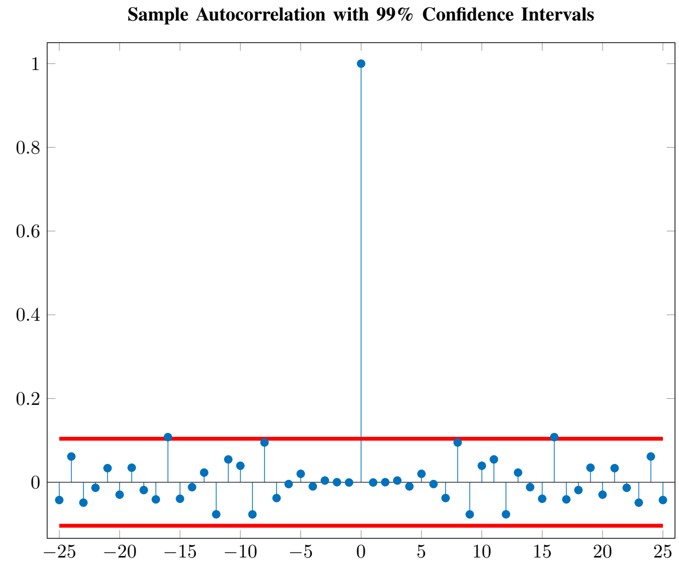

Fig. 7: Residuals of identified transfer function using data from PMU

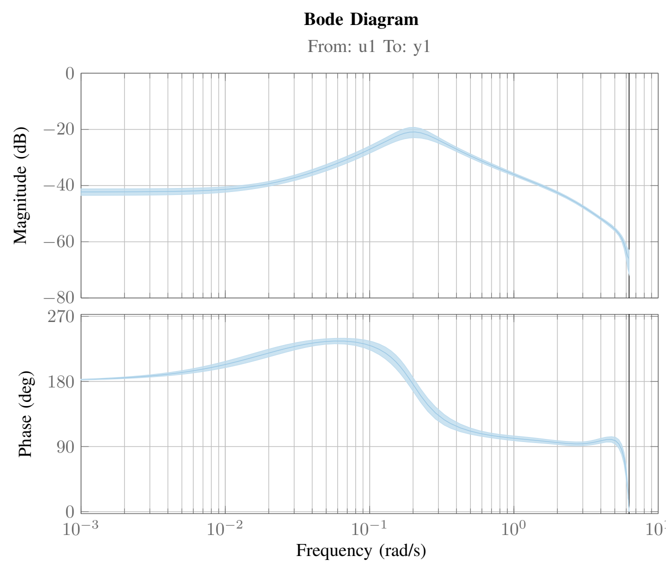

Fig. 8: Bode plot of identified transfer function using data from PMU

can calculate the normalized root mean square error (NRMSE) given by the following equation.

$$\text{NRMSE} = 100(1 - \frac{||y[n] - \hat{y}[n]||}{||y[n] - \bar{y}||}) \tag{20}$$

where:

$y[n]$: is a measured output signal.
$\hat{y}[n]$: is a signal simulated using a $u[n]$ as the input signal to the identified model $G_1(z, \hat{\theta}_N)$.
$\bar{y}[n]$: is the average of $y[n]$.

The result of such a cross validation is presented in Fig. 5. One will see that the response of the estimated function follows the analytical one closely. One can also see that the NRMSE value is very high, further indicating that the model performs well.

Another useful test is the residual test for the model structure. This test is useful, because it gives information on whether or not the correct model structure was chosen. The idea behind the test is to take the autocorrelation of (13), with the autocorrelation defined by (21).

$$\hat{R}_{\epsilon}^{N}(\tau) = \frac{1}{N} \sum_{n=1}^{N-\tau} \epsilon[n+\tau, \hat{\theta}]\epsilon[n, \hat{\theta}] \tag{21}$$

From the proof for consistent results we recall that if $\mathcal{S} \in \mathcal{M}$ all the terms of (13) except for the first term will approach zero. This means that if $\mathcal{S} \in \mathcal{M}$ the autocorrelation of (13) will approach zero for all $\tau \neq 0$. For $\tau = 0$ it will approach the variance of $e_1[n]$. The idea behind the test is then to use this fact to plot values of $\hat{R}_{\epsilon}^{N}(\tau)$ for different values of τ against the 99% confidence interval. The results from the residual test is presented in Fig. 6, where one can see that the residues are within or close to the confidence interval. From this we can conclude that a good model structure was chosen.

V. Results using PMU measurements

Since some assumptions were made for both the analytical validation and the simulation results it is also useful to investigate whether or not one will get good results using data from a real power system. This was done by collecting data from a generation plant in the Norwegian power system using a PMU. The preparation of the data was done in the same way as for the simulation case. For the PMU data the following model order was selected $[4, 5, 6, 5, 0]$.

In Fig. 7 one can see that the residues are within an acceptable range. Since we don't know the actual model of the plant we can't compare the bode plot to an analytical

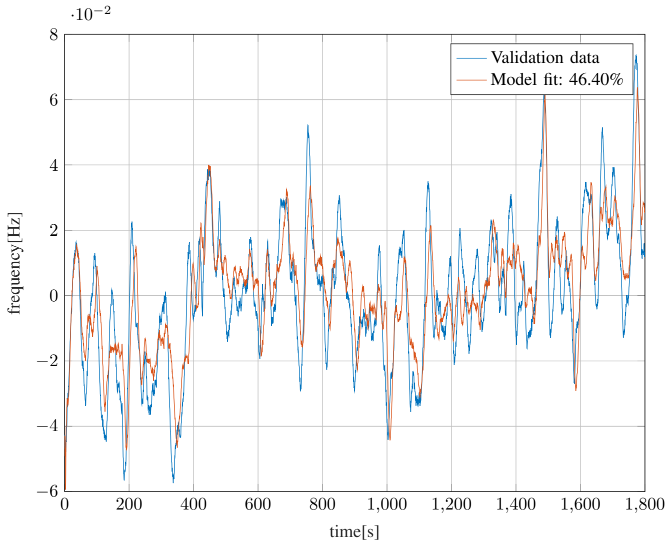

Fig. 9: Compare from PMU

function. However, one can still inspect the bode plot to see whether or not it look reasonable. It is clear from Fig. 8 that the obtained model resembles the one from the simulation validations. In addition the uncertainty corresponding to two standard deviations is shown in the plot. The confidence region of the model was calculated from the covariance of the parameter vector using the system identification toolbox in MATLAB [11]. For expressions for the covariance matrix one may refer to [9]. The plot shows that the uncertainty is rather low indicating that a decent estimate of the plant's dynamic behaviour has been obtained. However, as one can see from Fig. 9 we observe a low NRMSE that could be explained by a large noise power, but further analysis will be necessary.

VI. Conclusions

Several papers have already investigated system identification for identifying turbine and turbine governor dynamics using PMU measurements. However, no theoretical validation have been attempted before now. It was shown that the identification is indeed possible and that consistent results can be obtained. It is also worth noting that what one identifies is both the turbine dynamics including the governor as well as the electromechanical dynamics.

It still remains to investigate the implications on some of the assumptions made in this paper. However, the proposed method should provide a quick and easy method for TSOs to check whether or not production plants are well tuned, with respect to the droop settings and frequency response.

Acknowledgements

The work presented in this paper was carried out in the project OperaGrid funded by the Norwegian research council. In addition the ELECTRA IRP FP7 project funded the research exchange between NTNU and Ampere Lab.

References

[1] Statnett, Fingrid, Energinet.DK, and S. Kraftnät. (2016). Challenges and opportunities report, (visited on 08/30/2016).

[2] 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).

[3] 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.

[4] 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.

[5] S. H. Jakobsen and K. Uhlen, "Vector fitting for estimation of turbine governing system parameters," in *2017 IEEE Manchester PowerTech*, Jun. 2017, pp. 1–6. DOI: 10.1109/PTC.2017.7980855.

[6] B. Mogharbel, L. Fan, and Z. Miao, "Least squares estimation-based synchronous generator parameter estimation using PMU data," in *2015 IEEE Power Energy Society General Meeting*, Jul. 2015, pp. 1–5. DOI: 10.1109/PESGM.2015.7286559.

[7] 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.

[8] S. H. Jakobsen and K. Uhlen, "Development of a test system for identification of turbine dynamics using the dc power flow," presented at the Mathmod, Feb. 2018.

[9] L. Ljung, *System identification*. Springer, 1998. (visited on 03/29/2016).

[10] L. Saarinen, P. Norrlund, U. Lundin, E. Agneholm, and A. Westberg, "Full-scale test and modelling of the frequency control dynamics of the nordic power system," in *2016 IEEE Power and Energy Society General Meeting (PESGM)*, Jul. 2016, pp. 1–5. DOI: 10.1109/PESGM.2016.7741711.

[11] *System identification toolbox*, 2016. [Online]. Available: https://se.mathworks.com/products/sysid.html.