Identification of a system

Report of Laboratory Project

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`Predmet: Identification`
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Contents

Key words: ETFE, Orthogonal Corelation, LS, RLS, Instrumental variables, Stohastic aproximation, Extended LS, Maximum likelihood, Spectral analyis

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1 Tasks

- Choosing the apropriate excitation
- Signal processing
- Parametric model obtained with LS, RLS, IV, SA
- Non paramatric model obtained with ETFE, Spectral analysis
- Validation using Orthogonal correlation

2 Excitation for obtaining parametric model

For excitation signal we are choosing PRBS. PRBS signals contain a wide range of frequency components, enabling them to excite systems across various frequencies. PRBS has also the high Power Spectral Density (PSD) compared to other signals with bounded amplitude. PSD of PRBS is constant except at zero frequency. Using PRBS the system's response can be measured across a wide frequency range, providing valuable information for estimating the system's transfer function.

Our operating point will be 0.8 Volts. We will limit ourselfs to be between 0.8 and 1.2 volts for input signal since this corresponds to the linear region of our plant (fig. 1).

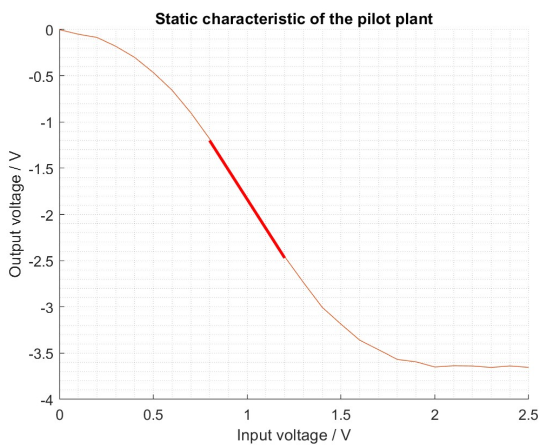

Fig. 1: Static characteristic of pilot plant

First we design a signal made of a step that last long enough that system stabilises in operating point. Then the PRBS signal is added. At the end the step signal of a amplitude of 1.2 volts, with short duration is added to capture better the lower frequencies.

For determining the order of the model it is crucial to choose the propriate sampling time. With a larger sampling time, we might miss critical information about the system's dynamics, while a smaller sampling time can introduce more noise into our model. We measured that the rise time is between 2 and 2.25 seconds. Usualy the sampling time is choosen to be arround $5 - 10$ % of the rise time. We chose it to be 0.2 s. After that we also experiment with other sampling times of 0.4 s and 0.1 s and obtained different results.

The shape of input signal is shown bellow

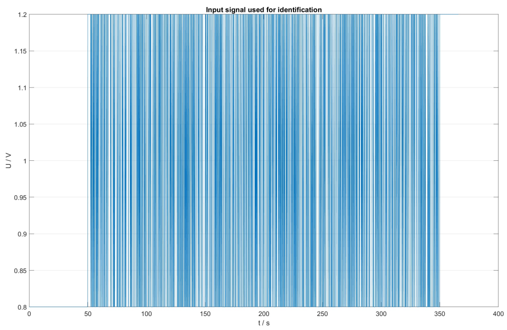

Fig. 2: PRBS input signal with short step at the end

After that we cut the ouptut and input signals, removing the first part where system stabilises. Part of cutted signal is then used to calculate the operating point which is substracted from the remaining signal.

3 Parametric modeling

3.1 LS

The method of least squares (LS) is a commonly used method for estimating the parameters of dynamic model. The goal of the method is to minimize the sum of squared differences between observed and predicted values.

First the strucutre of the model should be assumed and then the model should be constructed.

Consider a linear model for determining the dynamic process of the following form:

$$y = \Psi\hat{\theta} + e \tag{1}$$

where the Ψ is a matrix of delayed inputs and outputs writen as

$$\Psi^T = [-y(k-1) \ ... \ -y(k-n) \ u(k-1-d) \ ... \ u(k-n-d)] \tag{2}$$

where $y(k)$ is a output vector, $u(k)$ is the input vector and $e(k)$ is the error vector, n is the estimated order of a system, d is estimated delay of a system and $\hat{\theta}$ are estimated parameters.

The solution of LS for dynamic process is obtained by solving equation

$$\hat{\theta} = [\Psi^T\Psi]^{-1}\Psi^T y \tag{3}$$

Where $\hat{\theta}^T$ contains the parameters of the model $[\hat{a}_1, ..., \hat{a}_n, \hat{b}_1, ..., \hat{b}_n]$. ($\hat{y}(k) = -\hat{a}_1 y(k-1) - \cdots - \hat{a}_n y(k-n) + \hat{b}_1 u(k-d-1) + \cdots + \hat{b}_n u(k-d-n)$, the z-transform of the $\hat{y}$ is $\hat{y}(z) = [1 - \hat{A}(z^{-1})]y(z) + \hat{B}(z^{-1})z^{-d}u(z)$).

The inverse of $\Psi^T\Psi$ has to exist. This is done by using excitation that has rich frequency content such as PRBS.

For dynamical processes it is shown that the estimate $\hat{\theta}$ is bias free ($E\{\hat{\theta}\} = 0$) if the process output noise $n(k)$ is obtained by filtering white noise $v(k)$ through a noise filter $\frac{1}{A(z^{-1})}$. (The z-transform of error is writen as $e(z) = \hat{A}(z^{-1})y(z) - \hat{B}(z^{-1})z^{-d}u(z)$) This guarantees that the noise and the input signal are uncorrelated. Also either noise $v(k)$ or process input $u(k)$ should be zero mean ($y = \Psi\theta + v$). The estimate $\hat{\theta}$ is consistent in the mean square if the noise $v(k)$ is white.

By experimenting with different orders and delays for our system using LS, we find that the model best fits the training data when the estimated order is 4 and delay 0.

The change from 4. order to the 5. does not improve results drastically looking into MAE (Mean absolute error) and therefore for better generalization we take the fourth order and avoid fitting the noise in the data by selecting a higher order.

Results on the training data are shown on the following picture.

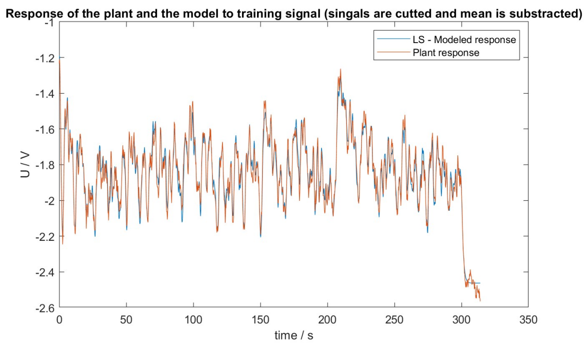

Fig. 3: Results obtained using LS on training data

Standard deviations of parameters are obtained by taking square roots of the diagonal elements of covariance matrix of parameters, which is calculated using the following expression:

$$cov[\hat{\theta} - \theta] = \frac{1}{(N - n - d) - 1} \sum_{k=n+d}^{N-1} ee^T(\Psi^T\Psi)^{-1} \tag{4}$$

```
LS std of parameters

std(a1) = 0.033574
std(a2) = 0.040477
std(a3) = 0.042114
std(a4) = 0.024505
std(b1) = 0.004421
std(b2) = 0.005014
std(b3) = 0.006610
std(b4) = 0.006126
```

Fig. 4: Standard deviations of parameters

The model is good if the excitations are large and the variances are small, that is, the SNR is large. The variances of parameters are smaller the more sensitive the error is to the parameters. Parameter can not be estimated if the error is independant of that parameter.

After the training we validated the obtained model writen in the discrete form

$$H(z) = \frac{-0.07278z^3 - 0.1478z^2 - 0.1222z - 0.05869}{z^4 - 0.6375z^3 - 0.372z^2 - 0.1014z + 0.2356} \tag{5}$$

or in the continuos time domain (converted using ZOH method)

$$G(s) = \frac{0.272s^3 - 6.718s^2 + 10.17s - 812.3}{s^4 + 7.228s^3 + 156.5s^2 + 394.3s + 252.2} \tag{6}$$

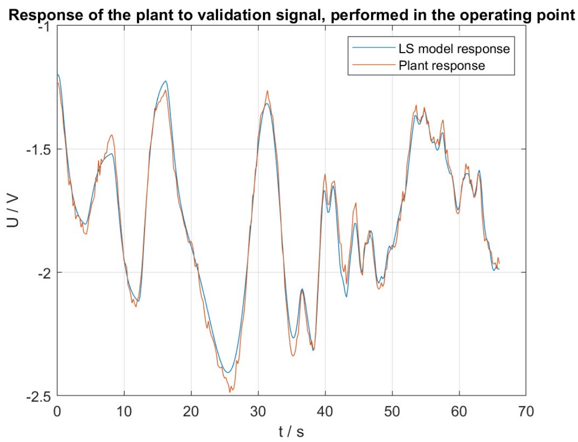

Fig. 5: Results of validation

Where the input signal used for validation was

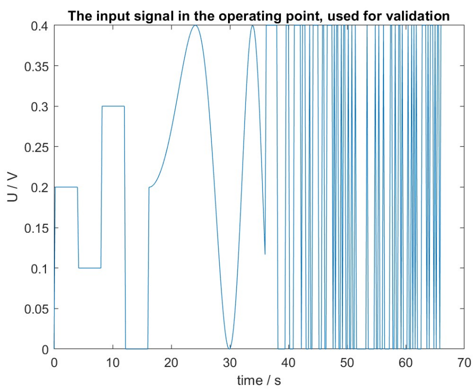

Fig. 6: Input signal in the operating point ($U_0 = 0.8$V) used for validation

The results obtained using LS method are quite good with the MAE of 0.033 Volts.

3.2 RLS

Recursive Least Squares (RLS) is an algorithm that provides an online solution to the least squares problem by recursively updating the coefficients as new data samples arrive. It is mathematical equivalent of the least squares method. The computation would be very time consuming if we would have to invert the matrix $\Psi^T\Psi$ every time new data comes, that is why we update estimate based on previous estimate without matrix inversion.

Recursive estimation for $\hat{\theta}$ is obtained by solving:

$$P(k+1) = \left(P(k) - \frac{P(k)\Psi(k+1)\Psi^T(k+1)P(k)}{\lambda(k+1) + \Psi^T(k+1)P(k)\Psi(k+1)}\right)\frac{1}{\lambda(k+1)} \tag{7}$$

$$\hat{\theta}(k+1) = \hat{\theta}(k) + P(k+1)\Psi(k+1)\left[y(k+1) - \Psi^T(k+1)\hat{\theta}(k)\right] \tag{8}$$

Where matrix P is of dimension $3n \times 3n$ and is proportional to $cov\{\hat{\theta}\}$. At the beginning of algorithm the elements of P are set to some large values like 1000. This initial setting implies a high uncertainty in the initial parameter estimates, indicating that the algorithm has limited confidence in these estimates. That is why the parameters will change a lot at the initial iterations. Ideally, as the algorithm processes more data points, the P matrix should converge to a steady-state value. This steady-state value represents the final uncertainty in the parameter estimates.

The coefficient λ is forgetting factor, which is useful in the case of time-varying system. With it, we achieve that the algorithm takes recent measurements into account more than the past ones.

In our case we experimented with different lambdas from interval of $0.95 < \lambda \leq 1$. The best results in terms of MAE (Mean Absolute Error) are obtained using lambda of 1, which is expected, because the forgetting is used for time-varying systems, meaning that its parameters change over time. Our system is not one of them.

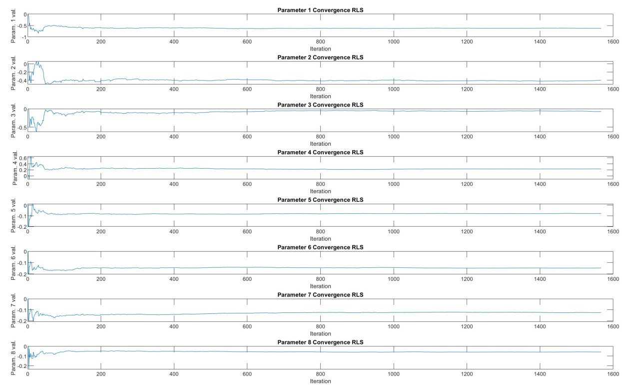

Fig. 7: Parameter values during iterations

Above we plotted how the parameter values change during iterations.

We can see, that parameters settle around 400 iteration, meaning that 400 data points are enough for estimating the parameters.

With the RLS we obtained following transfer function writen in discrete form

$$H(z) = \frac{-0.07278z^3 - 0.1478z^2 - 0.1222z - 0.05872}{z^4 - 0.6374z^3 - 0.3721z^2 - 0.1015z + 0.2356} \tag{9}$$

We can see, that transfer function is the same as the one obtained using LS (equation 5) which is no suprise, since the RLS algorithm is mathematical equivalent of LS. Some parameters only differ slightly on fourth decimal place, this could be due to numerical calculations and rounding errors.

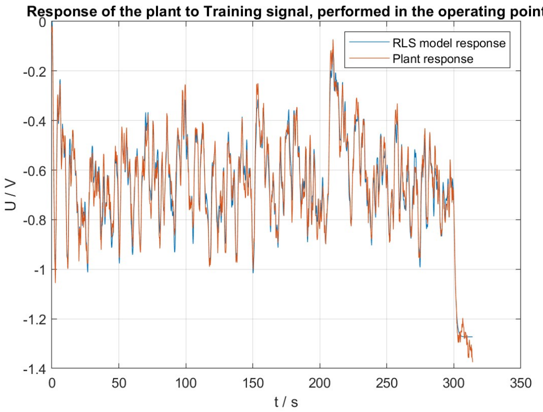

Fig. 8: Response to the training signal on fig. 2

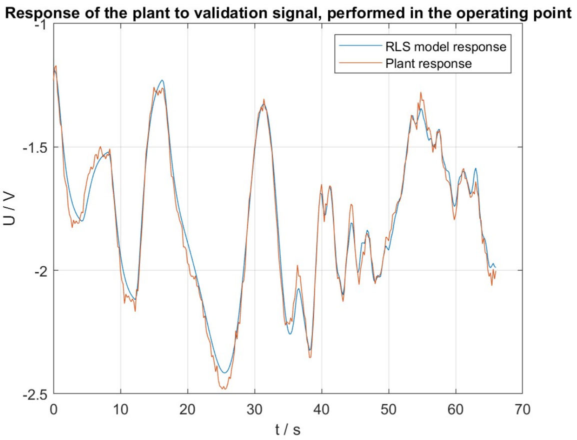

Fig. 9: Response to the validation signal on fig. 6

The MAE is the same as the one obtained using LS.

3.3 IV

The LS gives non biased results if the noise is filtered using special form of noise filter $1/A(z^{-1})$. Instrumental variables suppresses the bias by replacing measured output values y (corrupted with noise) with the instrumental variables x. IV x are not correlated with disturbance v and are highly correlated with the y. This second requirement is important to guarantee positive definitiveness of matrix $W^T\Psi$ which we will get to know promptly. With IV a more general noise is allowed but the price we pay is that stability is weaker.

Instead of multiplying equation $y - \Psi\theta = v$ with the Ψ^T, we pre-multiply with the W^T, the following estimate is obtained:

$$\hat{\theta} = \left[W^T\Psi\right]^{-1} W^T y \tag{10}$$

The bias is:

$$b = \left[W^T\Psi\right]^{-1} W^T v \tag{11}$$

If elements of matrix of instrumental variables W are uncorelated with noise v, the bias is 0. Matrix Ψ includes the input signals u that are uncorrelated with the noise and the signals y that are correlated with the noise n. Matrix W is constructed with undisturbed outputs, that are obtained by classical LS and input signals u as the Ψ matrix.

The algorithm is as follows

- 1. Construct Ψ from measuremants $u(k)$ and $y(k)$
- 2. Classical LS parameter estimation gives estimates $\hat{\theta}_{LS}$
- 3. Using $\hat{\theta}_{LS}$ the simulated output is obtained $y_s(k)$
- 4. Matrix W is constructed similary as Ψ but using y_s instead of y.
- 5. Parameter estimates according to instrumental variables are obtained $\hat{\theta}_{IV} = \left[W^T\Psi\right]^{-1} W^T y$

From step 5. we then return to step 3. but using the $\hat{\theta}_{IV}$ instead of $\hat{\theta}_{LS}$. This is done iteratively, until estimate $\hat{\theta}_{IV}$ settles.

We tried the algorithm and obtain the results only for the 1.,2., order. For higher orders the matrix $W^T\Psi$ becomes badly conditioned in some cases and the parameters can not be obtained (the alghorithm works about half of the time). So we add small regularization term αI to the matrix $W^T\Psi$ to make it better conditioned. The algorithem now works for higher orders. We obtained the following model in discrete form:

$$H(z) = \frac{-0.07246z^3 - 0.1476z^2 - 0.1204z - 0.05299}{z^4 - 0.6318z^3 - 0.4101z^2 - 0.09954z + 0.2636} \tag{12}$$

and in the continuos time domain (converted using ZOH method)

$$G(s) = \frac{0.1925s^3 - 5.985s^2 + 4.182s - 761.1}{s^4 + 6.666s^3 + 155.7s^2 + 357.6s + 236.5} \tag{13}$$

The response to the training signal is the following:

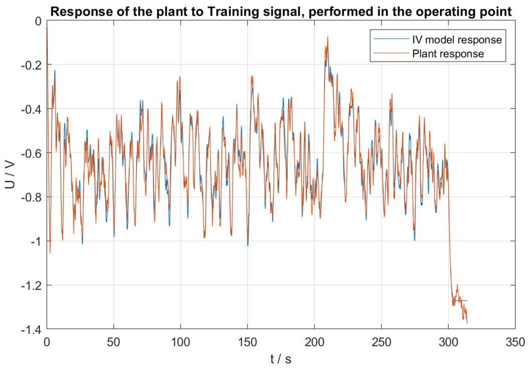

Fig. 10: Response to the training signal on fig. 2

The response to the validation signal is the following:

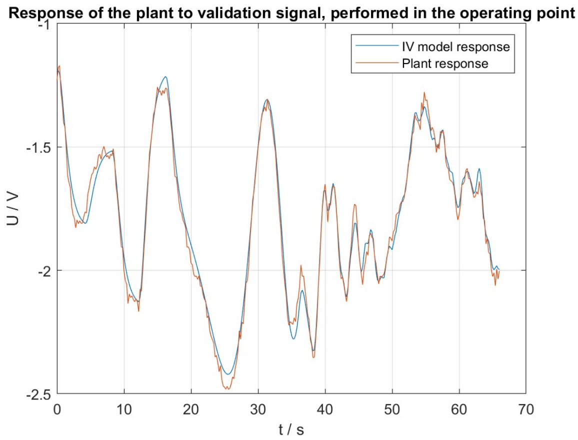

Fig. 11: Response to the validation signal on fig. 6

We obtain the MAE of 0.030 Volts. We can say that regularization did not effect the bias looking into MAE compared to MAE's of other methods.

Bellow we show how the parameters were changing through the iterations:

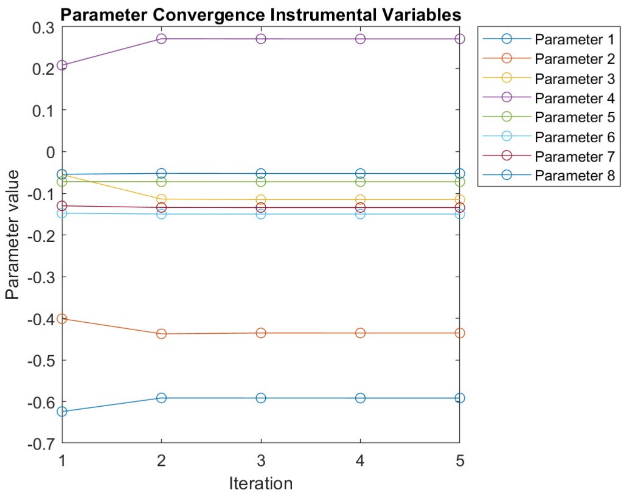

Fig. 12: Parameter values during iterations

We can see that it took 5 iterations for the parameters to settle.

3.4 STA

We also tried the stohastic approximation which uses gradient descent algorithm for minimisation of the cost function:

$$V(k+1) = \frac{1}{2}e^2(k+1) \tag{14}$$

Cost function only takes into account the current equation error:

$$e(k+1) = y(k+1) - \Psi^T(k+1)\hat{\theta}(k) \tag{15}$$

New parameter estimates are obtained by moving in the direction of the steepest descent of the cost function:

$$\hat{\theta}(k+1) = \hat{\theta}(k) - \rho(k+1)\frac{d}{d\hat{\theta}(k)}V(k+1) \tag{16}$$

Parameters are then calculated using the formula:

$$\hat{\theta}(k+1) = \hat{\theta}(k) + \rho(k+1)\Psi(k+1)\left[y(k+1) - \Psi^T(k+1)\hat{\theta}(k)\right] \tag{17}$$

The alghorithm is similar to RLS but instead of matrix P the scalar ρ is used.

For $\rho(k)$ we choose $\rho(k) = \frac{1}{k}$ which fulfils the requirements $\lim_{k\to\infty}\rho(k) = 0$, $\sum_{k=1}^{\infty}\rho(k) = \infty$ and $\sum_{k=1}^{\infty}\rho^2(k) = \infty$.

STA method is computationaly less demanding than RLS but it has slower parameter convergence. This can be seen by setting the initial parameters to zeros. How parameters are then changing can be seen on figure below.

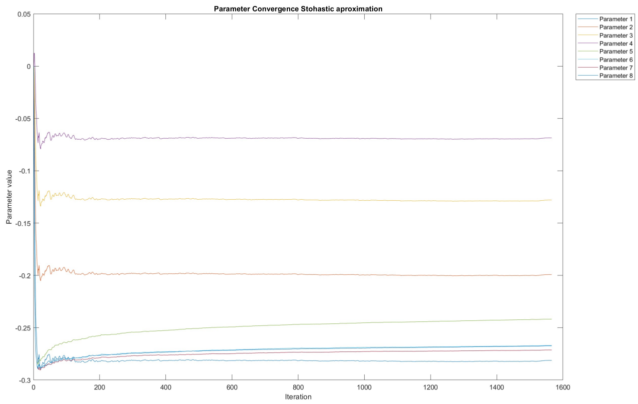

Fig. 13: Parameter values during iterations

We can see that the parameters have not settle down (in contrast to Stohastic aproximation parameters, RLS parameters needed 400 samples to settle). Using other initial parameters like $0.8\cdot\hat{\theta}_{LS}$, the parameters are able to settle down as shown bellow. They settle arround the 100 iteration.

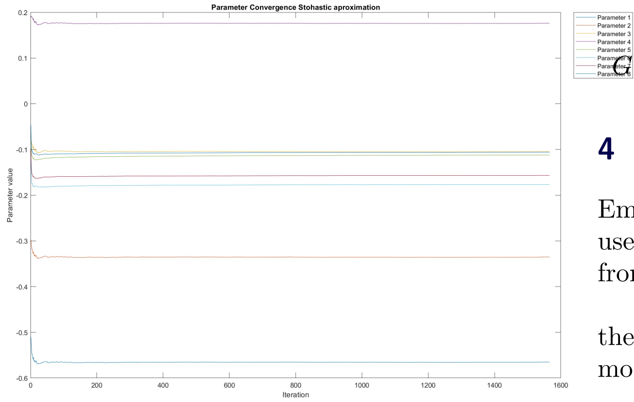

Fig. 14: Parameter values during iterations

We also obtain better MAE in second case which decreased from 0.070 to 0.041.

The response to the training signal is the following:

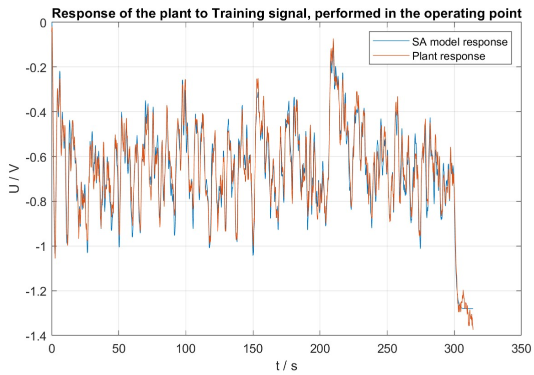

Fig. 15: Response to the training signal on fig. 2

The response to the validation signal is the following:

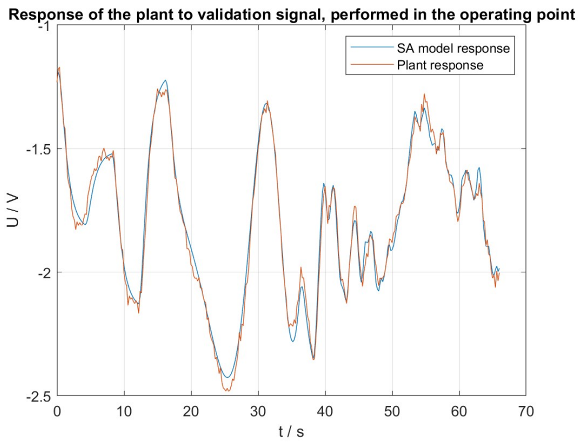

Fig. 16: Response to the validation signal on fig. 6

Obtained model writen in discrete form

$$H(z) = \frac{-0.1121z^3 - 0.1766z^2 - 0.1567z - 0.1061}{z^4 - 0.5651z^3 - 0.3354z^2 - 0.1044z + 0.1762} \quad (18)$$

and in the continuous time domain

$$G(s) = \frac{0.7746s^3 - 13.89s^2 + 36.21s - 1274}{s^4 + 8.681s^3 + 164.7s^2 + 534.6s + 395.8} \quad (19)$$

4 Non parametric modeling

Empirical Transfer Function Estimate (ETFE) is a method used to estimate the frequency response of a system from input-output data.

For excitation signal we are choosing PRBS that is the same as in previous task for determining parametric model described in chapter 2.

We peform the ETFE using formula:

$$G(j\omega) = \frac{Y(\omega)}{U(\omega)} \quad (20)$$

Since the output signal $y(t)$ is corrupted with some aditive disturbance $n(t)$

$$y(t) = y_0(t) + n(t) \quad (21)$$

and the frequency response of system is:

$$G(j\omega) = \frac{\mathcal{F}\{y_0(t) + n(t)\}}{\mathcal{F}\{u(t)\}} = G_0(j\omega) + \Delta G_n(j\omega) \quad (22)$$

we will estimate the standard deviation of the error of the amplitude-response estimate due to noise ($|\Delta G_n(j\omega)| = \frac{|N(\omega)}{|U(\omega|}$).

It is said that estimation using ETFE is un-biased if the noise $n(t)$ is not correlated with the input signal $u(t)$ and undisturbed output $y_0(t)$, and its mean value is 0. Also the condition $U(\omega) \neq 0$ should be met. When examining the consistency in the mean square, the variance of frequency-response error at certain frequency ω increases with power spectral density of the noise at ω, it increases with longer observation interval and decreases with higher power spectral density of the input at ω. It also applies here that the variance is theoreticaly unbounded where $U(\omega) = 0$.

The noise was taken in the operating point and is as long as signal used for ETFE.

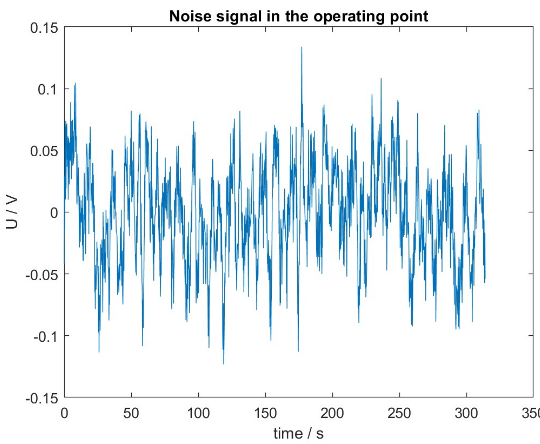

Fig. 17: Noise taken in the operating point, where mean was subtracted

We calculate the absolute value of the Fourier Transform of the noise $|N(\omega)|$. We see that the noise is coloured. After that we construct the model of the colour noise and calculate the standard deviation of the error of the amplitude-response estimate due to noise.

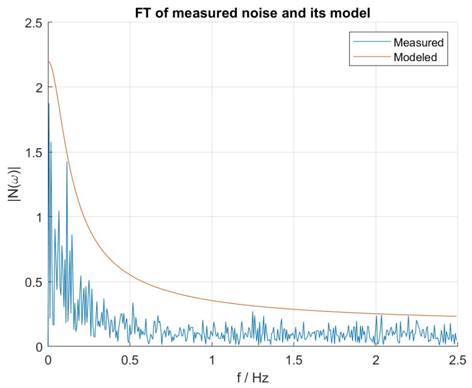

Fig. 18: FT of noise and its model

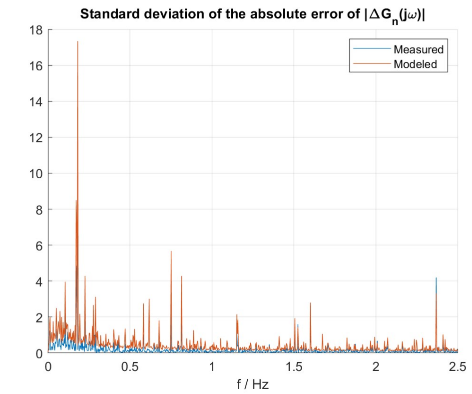

Fig. 19: The measured and modeled standard deviation of the error of the amplitude-response estimate due to noise $(|\Delta G_n(j\omega)| = \frac{|N(\omega)|}{|U(\omega|})$

Bellow we plot the results of the ETFE with its lower and upper bound obtained using the standard deviation of the error of the amplitude-response estimate due to noise.

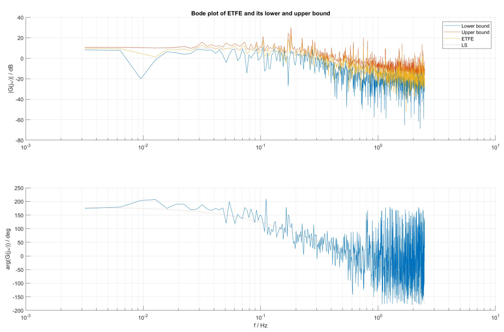

Fig. 20: Results obtained using ETFE

The phase looks very noisy, but this is caused by our unwraping function not working alright using noisy data (Matlab's built-in unwrap function was not useful in this case, so we had to construct our own).

The frequency resolution is $F = \frac{1}{NT}$ where N is lenght of signal vector and T the sampling time. The maximum frequency $f_{max} = \frac{1}{2T}$.

4.1 Orthogonal Correlation

The method of Orthogonal Correlation relies on estimating only one point of frequency response using one experiment. We are using cosine input singals of the following form: $u(t) = U_0 cos(\omega_0 t) + U_{00}$ Where $U_{00} = 1$ V is used to to bring the system to the linear area on static cahacteristic curve near the operating point. For amplitude of singal U_0 we choose 0.2 V. We calculate 11 harmonic frequencies for our experiments ($\omega_0 = 2 \cdot \pi \cdot f$). For the middle one we choose the cut-off frequency of $f = 0.125Hz$. We calculate real and imaginary points of each frequency response obtained by taking into account equations for correlation functions:

$$\Re[G(j\omega_0)] = \frac{2}{U_0 n t_p} \int_0^{n t_p} y(t) cos(\omega_0 t) dt \tag{23}$$

$$\Im[G(j\omega_0)] = \frac{-2}{U_0 n t_p} \int_0^{n t_p} y(t) sin(\omega_0 t) dt \tag{24}$$

For this method, the sampling time should be chosen much smaller (We chose $T_s = 0.001$), since the method relies on accurately capturing the high-frequency content of the input-output relationship. By using a smaller sampling time, wee can better resolve the fast dynamics of the system and obtain more accurate estimates of the frequency response.

The estimation is bias free if the noise is not correlated with the input and the latter is zero-mean. Estimation is consistent in the mean square if the noise is colour. Consequently the variance approaches 0 as observation time approaches infinity. Orthogonal Correlation can thus serve us for validation of ETFE. Below we show the results of it.

The durations of signals are set to be 100 s long. Which is long enough to capture enough periods even for lower frequencies, which defines the variance error (the more periods of output signal, the better).

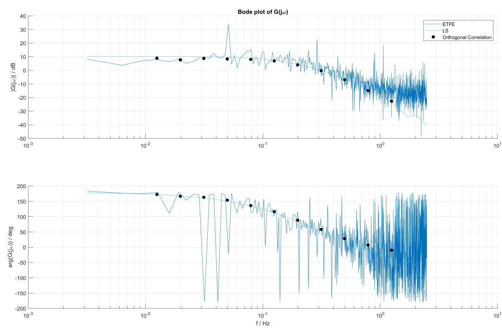

Fig. 21: Results of orthogonal corelation

4.2 Spectral analysis

We saw that the ETFE is very sensitive to noise. So we try to obtain the $G(j\omega)$ using the correlation functions. But we know that correlation functions have high uncertanty for large shifts τ, but FT puts equal gains to all samples of correlation functions. Solution is to filter the PSDs. Since the windowing used on corelation functions is equivalent to filtering PSD's in frequency domain we can write:

$$\Phi_{uy}^{W}(\omega) = \mathcal{F}[\phi_{uy}(\tau)w(\tau)] = \int_{-\infty}^{\infty} \Phi_{uy}(\omega)W(\omega_0 - \omega)\, d\omega \tag{25}$$

$$\Phi_{uu}^{W}(\omega) = \mathcal{F}[\phi_{uu}(\tau)w(\tau)] = \int_{-\infty}^{\infty} \Phi_{uu}(\omega)W(\omega_0 - \omega)\, d\omega \tag{26}$$

We are using Hann's window.

$$w(\tau) = \begin{cases} \frac{1}{2}[1 + cos(\frac{\pi\tau}{T_M})], & |\tau| \leq T_M \\ 0, & |\tau| > T_M \end{cases} \tag{27}$$

For window width T_M we were trying with different values. The width should be long enough to capture majority of information but short enough to neglect large shifts.

We choose one tenth of the length of correlation functions $\phi_{uy}(\tau)$,$\phi_{uu}(\tau)$, since we were satisfied with smoothed out frequecy response.

The results obtained are shown below.

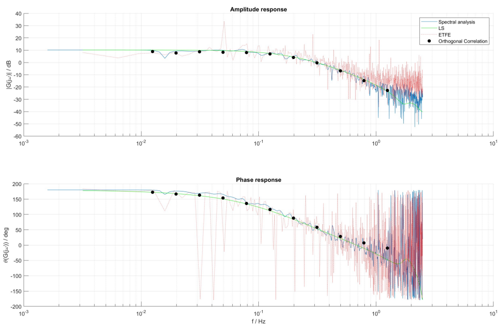

Fig. 22: Results of spectral analysis

We can see that we obtain results that have less noise compared to ETFE and are closer to the results obtained using LS and orthogonal correlation.

5 Discussion about sampling time

5.1 Sampling time of 0.4 seconds

As we mentioned at beggining, we also experimented with different sampling times. The sampling time of 0.4 seconds is arround 20 % of the rise time which is in our case carefully measured to be arround $2 - 2.25$ seconds. The sampling time of $T_s = 0.4$ s provides slightly better results in terms of MAE (Mean absoulte error) for parametric models using 4. order assumption. The difference in MAE was around 0.002 compared to $T_s = 0.2$ s. With this sampling time also the estimated order of 2 yields good results (MAE for LS obtained on validation signal is 0.033). Looking into the plots of frequency responses (obtained using ETFE, Spectral analysis and LS using assumption of 2. order), we get good matching for lower frequiencies but the higher frequencies are worse compared to the results obtained using $T_s = 0.2$ s.

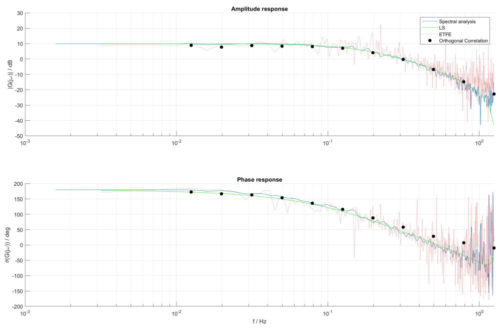

Fig. 23: Results for ETFE, Orthogonal correlation, spectral analysis and LS using assumption of 2. order for $T_s = 0.4$

Looking into fig 22. and 23. we see, that the parametric model obtained using $T_s = 0.2$ s and of the 4. order yields better results.

But using $T_s = 0.4$ we obtain a simpler model with fewer parameters. Simpler models are generally easier to implement and can be more computationally efficient. If the performance difference between the two models is not significant, the simpler model might be preferred.

The discrete transfer function of second order system obtained using LS where $Ts = 0.4$:

$$H(z) = \frac{-0.2671z - 0.2749}{z^2 - 1.163z + 0.3354} \tag{28}$$

```
std(a1) = 0.016254
std(a2) = 0.015125
std(b1) = 0.006323
std(b2) = 0.007733
```

Fig. 24: std's of parameters

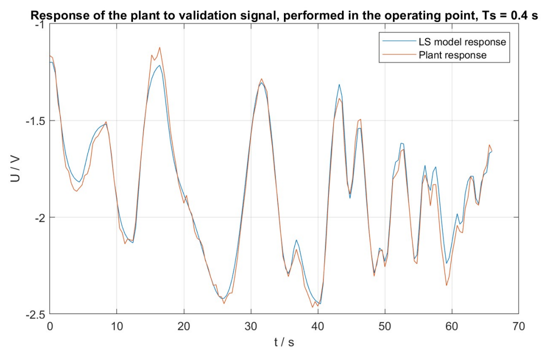

Fig. 25: Response to the validation signal on fig. 6

The MAE on validation signal is 0.033.

IV provides MAE of 0.030 for a validation signal. Transfer function obtained using IV is following

$$H(z) = \frac{-0.2682z - 0.2746}{z^2 - 1.197z + 0.3651} \tag{29}$$

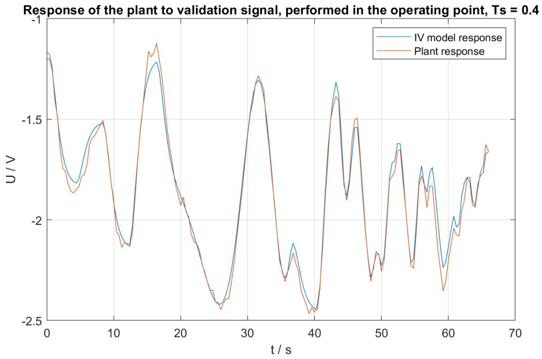

Fig. 26: Response to the validation signal on fig. 6

Also SA provides good results with MAE of 0.039 (Initial parameters are set as $0.8 \cdot \hat{\theta}_{LS}$).

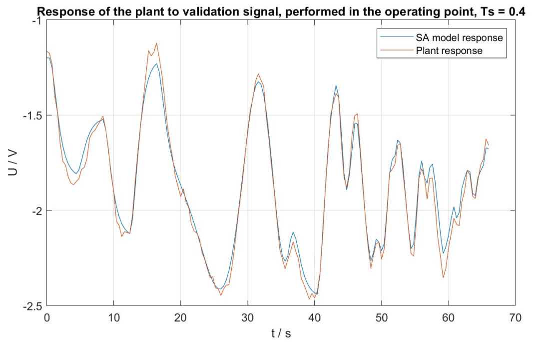

Fig. 27: Response to the validation signal on fig. 6

The discrete transfer function is following:

$$H(z) = \frac{-0.2965z - 0.316}{z^2 - 1.019z + 0.2074} \tag{30}$$

5.2 Sampling time of 0.1 seconds

Using lower sampling time of $T_s = 0.1$ s we obtain much worse results for parametric models obtained using LS and RLS. MAE on validation was arround 0.08 using assumption of 4. order. Smaller T_S introduced more noise into our model. But for IV we get similar results as using $T_s = 0.2$, where MAE on validation was arround 0.03 (Assumtion of 4. order as before).

Similiar for stohastic aproximation, where MAE was around 0.04, but using initial parameters set to $0.8 \cdot \theta_{LS}$. Using initial parameters set to 0, the MAE was much worse (0.080), since the parameters did not settle as shown in chapter 3.4. We see that some apriori knowledge about parameters is very useful for SA method.

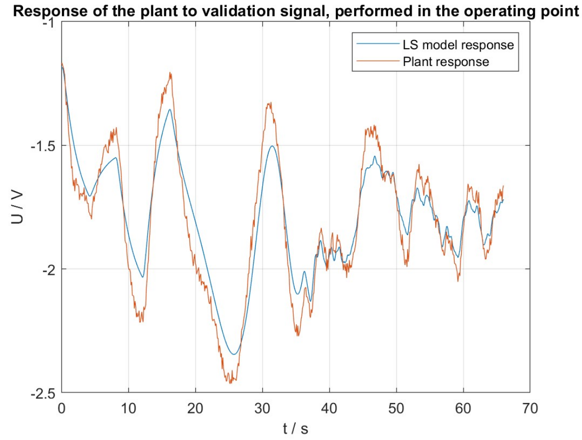

Fig. 28: Results of validation for LS using $T_s = 0.1$s using assumption of 4. order

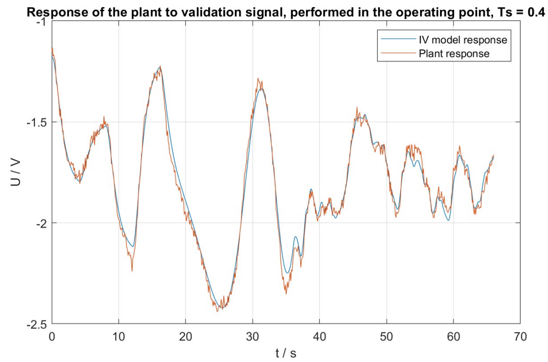

Fig. 29: Results of validation for IV using $T_s = 0.1$s using assumption of 4. order

These results highlight the robustness of the SA and IV methods in the presence of noise, making them preferable choices for system identification when dealing with noisy data or when using smaller sampling times.

The results for non-parametric models using $T_s = 0.1$ are better compared to the other sampling times.

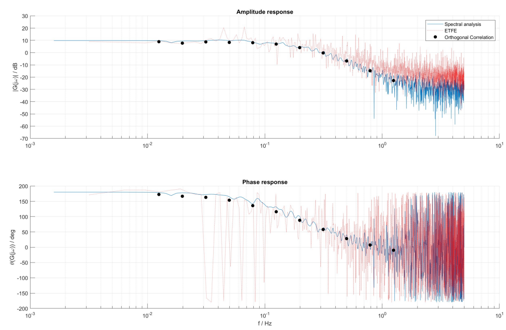

Fig. 30: Results for ETFE, Orthogonal correlation and spectral analysis for $T_s = 0.1$

6 References

1 Sašo Blažič, slides from lectures and literature for practicals

(For getting all the results with $T_s = 0.4$ s and estimated order of 2, the code from line 870 to the end, should be uncommented.)