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SYSTEM IDENTIFICATION PROCEDURES FOR RESONANCE FREQUENCY CONTROL OF SC CAVITIES*

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Abstract

Energy Recovery Linacs promise superior beam quality—smaller emittance and higher intensity. To reach these goals, resonance frequency control of the superconducting RF cavities has to be optimized.

To ensure stability of the resonance frequency the helium pressure inside the cryomodules is measured and stabilized. In order to improve the performance of the applied controller, i. e. for optimizing its parameters, one has to obtain the system's transfer function by means of physical modelling or system identification techniques. In this work the latter approach is presented. Special constrictions are the necessity to run the system in closed-loop mode and using data obtained during normal machine operation.

The results of system identification procedures conducted at the helium-pressure stabilizing system of the S-DALINAC's cryomodules (Institute for Nuclear Physics, TU Darmstadt, Germany) and first results of a test with improved control parameters are shown.

MOTIVATION

Due to their narrow bandwidth SC cavities are very sensitive to changes in their geometry. A 1 mbar pressure change of the helium in the cryomodules for example can cause a change in the resonant frequency of 20 to 50 Hz. Resonance frequency control with e. g. piezo tuners can be used to counteract this [1]. Another approach can be eliminating the sources of some disturbances, like decoupling the cryomodules from mechanically vibrating components such as vacuum pumps. Nevertheless, if there is for example a sudden heat intake, maybe due to turning on the RF power delivery to the cavities (or vice versa, lesser heat intake if one has to turn them off), this can cause more helium to evaporate (or less, respectively) and thus resulting in fluctuations of the helium pressure that have to be damped by the controller by increasing (or decreasing) the pump's speed.

Figure 1 shows a typical measurement of the helium pressure when such a disturbance occurs. The system is operated in closed-loop mode so that the controller damps the disturbance to reach the steady state. At the S-DALINAC this process can take up to three hours, as on can see in Fig.1.

Although this is a rather slow process it causes drifts that have to be compensated by the piezo tuners. Since these feedback loops rely on the measurement of the RF phase, they can have problems detecting such slow changes and sometimes manual corrections to the RF phase are applied by the operators who recognize e. g. a drift in the beam energy. To improve long-term stability of the beam quality and to ease the operation of the machine, an improvement of the helium pressure stabilizing controller was desired.

There have been some tests modifying the controller's parameters—it's a standard PID controller with $P = 250,\ I = 3\,\mathrm{s},\ D = 0\,\mathrm{s}$:

$$U(t) = PE(t) + \frac{1}{I}\int_0^t E(t')\mathrm{d}t' + D\frac{\mathrm{d}E(t)}{\mathrm{d}t}. \qquad (1)$$

Especially the D-component was slightly increased to speed up the system, but no results were found in the tested parameter range. To ensure stable operation this range was chosen very narrow.

With the model obtained from system identification an improved set of control parameters was suggested and successfully tested.

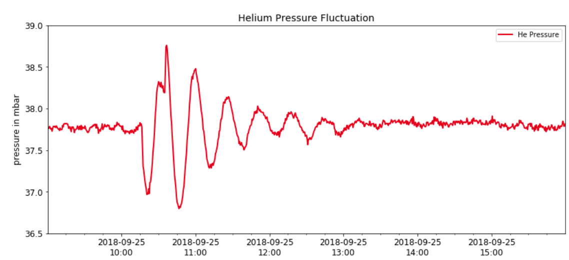

Figure 1: Helium pressure fluctuation in a cryomodule after a disturbance.

This system identification was also intended to serve as a prove of principle for closed-loop system identification procedures that are planned to be applied to other components as well. To make this transfer more convenient a generalized description of the system will be given in the next section followed by an overview over different closed-loop system identification techniques and a their advantages and disadvantages. Then, the results of such an identification process applied to the helium pressure stabilizing system and simulations with improved control parameters are shown. These predictions have been tested and first measurement results are presented.

BLOCK DIAGRAM AND SYSTEM EQUATIONS

The block diagram of a closed-loop system is depicted in Fig. 2. Note that for an open-loop system identification there is no feedback of the system's output y and in many cases the identification directly uses the system's input u. Also

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for closed-loop system identification one can make use of an exiting signal r_1 that directly acts on the plant. In normal operation this signal r_1 typically is not present.

Measurements of u and y are mandatory, while exact knowledge of r_1 or r_2 or knowledge of C is not required in general but can be necessary for some identification schemes.

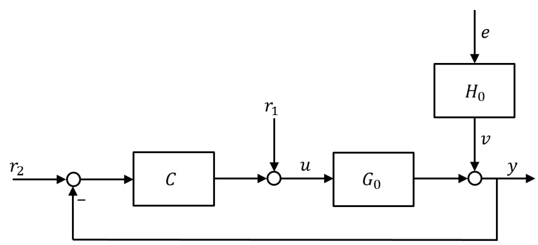

Figure 2: Block diagram of a closed-loop system with a controller C, the plant G_0, reference signals r_1 and r_2 and noise v.

The system's output $Y(t)$ is assumed to be digitally sampled with a constant sampling time T with $Y_k := Y(kT)$, $k = 0, 1, \ldots$ and hence the system is described in its z-transform with z being the forward shift operator,

$$Y_k \circ\!\!-\!\!\bullet\; y(z) \quad (2)$$

$$Y_{k+1} \circ\!\!-\!\!\bullet\; z \cdot y(z). \quad (3)$$

Following [2] the exciting signals are combined to

$$r = r_1 + C(z) r_2. \quad (4)$$

The noise v is modelled as filtered white noise,

$$v = H_0(z) e, \quad (5)$$

where $H_0(z)$ has to be stable and stably invertible. The noise disturbance will be assumed to be uncorrelated with the signals r_1 and r_2. The system's sensitivity function is

$$S_0 = (1 + G_0 C)^{-1} \quad (6)$$

where the argument is omitted for better readability.

This results in the following system equation and feedback law:

$$y = S_0 G_0 r + S_0 H_0 e, \quad (7)$$

$$u = S_0 r - S_0 C H_0 e. \quad (8)$$

CLOSED-LOOP SYSTEM IDENTIFICATION

The aim of the identification process is to obtain a model (an estimate) of the plant G_0 and possibly also the noise filter H_0 or also the controller C. When one already knows the controller C knowledge of the set-point signal r_1 and extra input r_2 brings no additional information if u is measured [3] and vice versa. In practice however, delimiters and other nonlinearities can occur and thus the controller won't have the simple form one could assume if e. g. the PID parameters are known. Thus even for seemingly simple controllers it can be beneficial to identify them as well.

In this contribution the focus will be on parametric system estimation. Since there is an important difference to the open-loop case, it shall be mentioned that while in the open-loop case a non-parametric (spectral) estimate $\hat{G}(e^{j\omega})$ can be obtained from the spectra of the input and output data, $\hat{G}(e^{j\omega}) = \frac{\hat{\Phi}_y}{\hat{\Phi}_u}$, this is no longer valid when the loop is closed and will result in a weighted average between G_0 and $-\frac{1}{C}$ [2]. To avoid this, one has to provide an external excitation via r and use the cross-spectra to obtain an unbiased estimate via

$$\hat{G}(e^{j\omega}) = \frac{\hat{\Phi}_{yr}}{\hat{\Phi}_{ur}}. \quad (9)$$

In parametric spectrum estimation the closed-loop case is rearranged in such a way that open-loop methods can be applied. Different approaches are often grouped into the so-called direct and indirect methods, but it can be shown [3] that from the estimator's point of view they differ only in the parametrization of the noise model. Nevertheless this distinction is useful to understand the advantages and restrictions that come with the different approaches.

In the following we will only consider rational transfer functions of the form

$$G(z) = \frac{b_{n-1} z^{-1} + \ldots + b_0 z^{-n}}{1 + a_{n-1} z^{-1} + \ldots + a_0 z^{-n}} = \frac{A(z^{-1})}{B(z^{-1})} \quad (10)$$

($H(z)$ analog) with polynomials $A(z^{-1})$, $B(z^{-1})$, ..., with a priori known order n and without delay. The parameters a_i, b_i, ... are combined into a parameter vector θ.

Direct Identification

The most simple solution is to "ignore" the fact that the feedback path is closed and identify a transfer function from u to y by defining the equation error

$$\tilde{\epsilon}(\theta) := y - G(z, \theta) u \quad (11)$$

and minimizing

$$J = \tilde{\epsilon}^{\mathrm{T}} \tilde{\epsilon} \quad (12)$$

to obtain $\hat{\theta}$, which is a least squares problem. This method generally works if the noise v (present in y) is uncorrelated with u. For closed-loop systems this is not the case and thus in general a very high signal-to-noise ratio (SNR) at the plant input u is required to mitigate the bias. In the special ARX-case, i. e. when the noise filter is given as $H(z) = \frac{1}{A(z^{-1})}$, then $G(z, \hat{\theta})$ will be a bias-free and consistent estimator (a Python package that implements system identification algorithms for the ARX- and also the more general ARMAX-case is SIPPY [4]).

To overcome this restriction one can use the *prediction error* instead of the equation error,

$$\epsilon(\theta) := H^{-1}(z, \theta)\,(y - G(z, \theta) u) \quad (13)$$

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and minimize

$$V = \epsilon^{\mathrm{T}}\epsilon \tag{14}$$

to obtain $\hat{\theta}$. This method results in estimates $G(z,\hat{\theta})$ for the plant and $H(z,\hat{\theta})$ for the noise which will be bias-free and consistent if the whole system $S := (G_0, H_0)$ is present in the chosen model set $\mathcal{M} := \{(G(z,\theta), H(z,\theta)),\ \theta \in \Theta\}$. This means, a rich model set has to be chosen, especially for modelling the noise and thus this method is not suitable if one is interested in reduced-order (approximate) model identification.

Note that the direct identification methods described above do not require knowledge of the controller C but also they do not benefit from knowing C.

Indirect Identification

The general idea behind the indirect identification methods is to identify the closed-loop system's transfer function $G_{\mathrm{cl}} = \frac{G_0}{1+G_0C}$ or the system's sensitivity function $S_0 = \frac{1}{1+G_0C}$ and to extract the plant's transfer function from these estimates. Whether G_{cl} or S_0 is to be identified, in either case the identification makes use of the signal r instead of the plant's input u and thus benefits from the fact that r and the noise v are uncorrelated. Using e. g. the prediction error method one can estimate G_{cl} from

$$y = G_{\mathrm{cl}}(z,\theta)r + H_{\mathrm{cl}}(z,\theta)e \tag{15}$$

and with knowledge of C an estimate for G_0 is obtained as

$$G(z,\hat{\theta}) = \frac{\hat{G}_{\mathrm{cl}}}{C(1-\hat{G}_{\mathrm{cl}})}. \tag{16}$$

Equation (16) typically results in a high-order model and exact knowledge of C is required. For lower-order models special parametrizations of the estimated transfer functions can be chosen to avoid the calculation of Eq. (16). One possibility to do so is the coprime factor identification [2].

If one wants to ensure that the identified model will definitely be stabilized by the given controller C one can chose the dual Youla-Kučera parametrization [2].

To identify the system without knowledge of C and for precise control of the desired model order the two-stage methods can be applied [2]. In this approach one rewrites the system's equation (7) and the control law Eq. (8) introducing a *noise-free* input $u_r := S_0 r$ ending up with

$$y = G_0 u_r + S_0 v, \tag{17}$$
$$u = u_r - S_0 C v, \tag{18}$$
$$u_r = S_0 r. \tag{19}$$

The first step is then to identify the system's sensitivity function S_0 from

$$u = S(z,\beta)r_1 + W(z,\beta)e \tag{20}$$

(in the case where r_2 is used instead of r_1 the function $S(z,\beta)$ estimates CS_0 and the result is the same [2]) applying open-loop techniques like the prediction error method or simple least squares with the equation error (since r_1 and e are uncorrelated the estimator will be bias-free and consistent). With $S(z,\hat{\beta})$ one can simulate the noise-free input $\hat{u}_r$ with Eq. (19).

In the second step G_0 can be estimated from Eq. (17) again with e. g. the prediction error method with

$$\epsilon(\theta) = K^{-1}(z,\theta)\,(y - G(z,\theta)\hat{u}_r)\,, \tag{21}$$

benefitting from the fact that u_r and noise v in Eq. (17) are uncorrelated. One finally obtains the estimates

$$\hat{G}_0 = G(z,\hat{\theta}), \tag{22}$$
$$\hat{H}_0 = K(z,\hat{\theta})S^{-1}(z,\hat{\beta}). \tag{23}$$

The estimators will be bias-free and consistent if S_0 lies within the chosen model set for $S(z,\beta)$, so a high-order estimate should be used to find an unbiased estimate $\hat{S}_0$ [3].

The high-order estimate of $\hat{S}_0$ will not result in a high-order estimate of $\hat{G}_0$ because since there are no constraints on $G(z,\theta)$ in Eq. (21) the model order is fully under control [2].

Additionally, no knowledge of C is required.

IDENTIFICATION OF THE HELIUM PRESSURE STABILIZING SYSTEM

Based on the helium pressure fluctuations after an impulse-shaped disturbance an indirect identification scheme based on reconstructing $\hat{G}_0$ from Eq. (16) was performed. To avoid high-order estimates the system was set up as a PT2 system with one zero to allow for the jump that was present in the data. The controller C was modelled as standard PID controller.

With these assumptions the transfer function of the plant in the Laplace-domain (complex variable $s = \sigma + j\omega$) is

$$\hat{G}_{\mathrm{He}}(s) = \frac{3.988 \cdot 10^{-5}s}{s^2 - 9.034 \cdot 10^{-3}s + 2.901 \cdot 10^{-6}}. \tag{24}$$

Simulation and Controller Improvement

Figure 3 shows a comparison of the measured data (red curve) and the simulated response of the system consisting of the controller C with the parameters $P = 250$, $I = 3\,\mathrm{s}$, $D = 0\,\mathrm{s}$ and $\hat{G}_{\mathrm{He}}$ from Eq. (24) in closed-loop operation (green curve) to an impulse-shaped disturbance. Additionally Fig. 3 includes a prediction of the system's response to the same impulse-shaped disturbance if a set of improved control parameters, $P = 300$, $I = 3\,\mathrm{s}$, $D = 1000\,\mathrm{s}$, is applied (blue curve). Using the D-part of the controller significantly increases the system's response time allowing it to return to steady-state in 20 % of the time it took before.

Since the D-part of the controller acts proportional to the frequency it also amplifies high frequency noise. To estimate the impact of the improved parameters Fig. 4 shows a simulation of the system's response to noisy input with the estimated response with the old parameters in green and with

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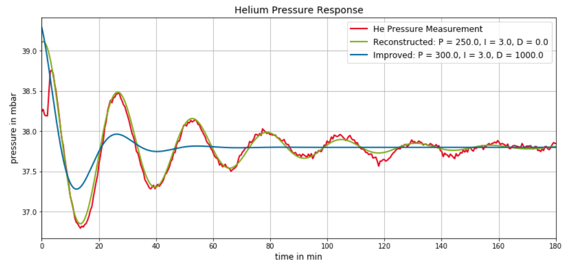

Figure 3: Comparison of the measured response of the helium pressure to an impulse-shaped disturbance (red), a simulation of the identified system to an accordingly modelled disturbance (green) and the simulated response of this model when improved control parameters are set (blue).

the new ones in blue. The red lines indicate that the peak values stay in the same range for both options and only the average noise power is higher. Note that the absolute value of the amplitude is much higher than in normal operation, but since the system is linear it can be scaled without distortion.

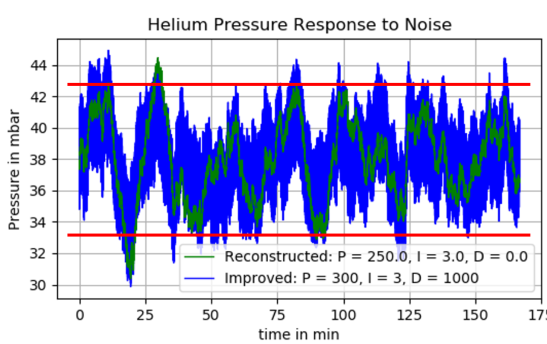

Figure 4: Simulation of consequences of the increased D-value for the system's reaction to noise. The red lines indicate that the amplitude stays within the same range.

MEASUREMENT RESULTS

To benchmark the simulation results it was planned to apply the improved control parameters to the system just before the maintenance shut-down in December 2018. Due to the warm-up process being already in preparation the helium-level inside the cryomodules was lower than during normal operation and three pumps running at idle reduced the pressure well below the set-point. To bring the system back to the working point one pump was turned off at 07:39 a.m., see Fig. 5. This disturbance caused an oscillation as was expected but since the controller still was set with the old parameters this oscillation should have been damped. As Fig. 5 shows, this wasn't the case, probably due to the mentioned circumstances. Nevertheless we decided to apply the improved parameters at 10:31 a.m. and with these new parameters a significant reduction in the amplitude of the oscillation was achieved.

So far, no further tests during normal operation were conducted.

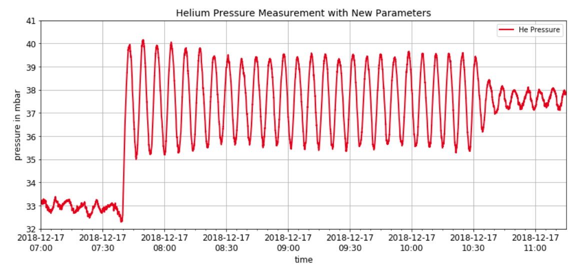

Figure 5: Measured helium pressure change when one of three running pumps is turned off (07:39 a.m.) and when the new control parameters are applied (10:31 a.m.). The remaining oscillation is still under investigation but is supposed to originate from the already very low Helium level due to the running shut-down process.

SUMMARY AND OUTLOOK

In this work different methods for closed-loop system identification have been summarized. They can be distinguished as direct and indirect methods, where direct methods make use of the plants in- and output u and y while indirect methods need an external reference signal r and the plant's output y. The choice between these methods is depending on knowledge of the controller C and the demands on the model orders of the plant and also the noise filter.

An indirect approach with assumed second order plant transfer function was carried out for the helium pressure stabilizing system of the S-DALINAC and simulations showed possible improvements for the PID controller's parameters. First tests with those parameters conducted just before the last maintenance shut-down gave promising results.

In the future, extended tests shall be carried out, including the application of different reference signals to be able to compare and benchmark the different approaches and to justify the assumptions.

Furthermore, these closed-loop system identification schemes can also be applied to more low-level RF components with data taken during normal operation. Thus, no beam time has to be omitted for testing and data generation.

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