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# Power-based control of output oscillations with online estimation of biased harmonics

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**Abstract:** The recently introduced discrete power-based control (Ruderman (2024b)) reduces largely the communication efforts in the control loop when compensating for the marginally damped or even slowly diverging output oscillations. The control commutates twice per oscillations period (at the amplitude peaks) and uses the measured harmonic output only. The power-based control scheme requires the knowledge of the instantaneous frequency, amplitude, and bias parameters of the harmonic signal. This paper extends the power-based control by the finite-time estimation of the biased harmonics (Ahmed et al. (2022)). Also an improved analytic calculation of the impulse weighting factor is provided. The power-based oscillations control with online estimation of the harmonic parameters is evaluated experimentally on the fifth-order actuator system with a free hanging load under gravity and measurement noise.

*Keywords:* Power based control, oscillations compensation, frequency estimation, biased harmonics, finite-time parameters estimation, discrete feedback control

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## 1. INTRODUCTION

The control, or often just a mitigation, of the harmonic oscillations and/or vibrations in the output state is an essential issue for various mechanical systems and application scenarios. Examples can be found in e.g. active suspensions (Landau et al. (2005)), off-shore rotary drilling systems (Wang et al. (2020a)), actuator drives with elastic connections (Ruderman et al. (2012)), two-rotor vibrational systems (Fradkov et al. (2020)), to mention here a few. The associated control problems are often exacerbated by the fact that sensor and actuator elements are not co-located, like in case of e.g. drill string systems (Aarsnes and van de Wouw (2018)) or large flexible structures (Gibson et al. (2011)). The non-collocated oscillatory systems can suffer under a limited access to the internal dynamic states and a poor observability, that makes an observer design and full-state feedback control hardly achievable, as demonstrated in Ruderman (2024a). If a non-collocated sensor/actuator configuration is in place, a reduced communication rate in the closed control loop can also be desired, cf. Ruderman (2024b). Such control with the reduced sampling or event-triggered may be advantageous in terms of the hardware components and communication architecture, but at the same time requires a reliable online estimation of the oscillation process parameters on the sensor side.

The problem of online estimation of parameters from a linear regression is classical and has many solutions depending on excitation of the regressor and the properties of measurement perturbations Ljung (1987); Sastry and Bodson (1989); Astolfi et al. (2008). A usual standing assumption requires the persistence of excitation (Morgan and Narendra (1977)) of the regressor for robust estimation in face of disturbances, while in the noise-free setting

the necessary and sufficient condition is the interval excitation. The most popular solutions include the least squares algorithm or the gradient descent one, which guarantee an exponential convergence of the estimates to their ideal values under a sufficiently excited regressor (Narendra and Annaswamy (1987)), while for a weaker excitation the asymptotic convergence rates can be recovered, see Efimov et al. (2019).

In the case when some parameters appear in a nonlinear fashion in the regression, there are methods oriented on estimation for convex/concave functions of the parameters (Fomin et al. (1981)) or other special scenarios (Tyukin et al. (2007); Ortega et al. (2024)). Recent approaches use some preliminary algebraic operations reducing the problem to a linear regression with respect to other parameters, see e.g. Ushirobira and Efimov (2023). A notable example here is the problem of estimation of a frequency in a measured biased harmonic signal, which has many solutions Pin et al. (2019); VEDIKOVA et al. (2020); Ahmed et al. (2022); Ruderman (2024a), to mention a few.

If the estimation algorithm represents a part with online control loop, then often stricter requirements on the rate of convergence and robustness are imposed. It has been observed, that in conventional approaches it is difficult to accelerate since their performance characteristics are governed by the level of excitation, Efimov and Fradkov (2015), which may be hard to change. Recently, several alternative solutions have been proposed, which however require more computational power Chowdhary et al. (2012); Aranovskiy et al. (2017), but they can provide finite/fixed-time convergence rates (Efimov and Polyakov (2021)) for the estimation errors in linear regressions (Ríos et al. (2017); Wang et al. (2020b)). An

example of the practical control scenario necessitating a rapid and reliable frequency estimation is the problem of compensating mechanical oscillations of a passive inertial load, that was recently addressed in Ruderman (2024a,b). Based thereupon, the present work combines the power-based control (Ruderman (2024b)) with the finite-time estimation of the biased harmonics (Ahmed et al. (2022)). The control scheme requires the knowledge of the instantaneous frequency, amplitude, and bias parameters of the output harmonic signal to be compensated.

The rest of the paper is organized as follows. In section 2, we resume the discrete power-based control (Ruderman (2024b)) and provides the impulse weighting factor by analytic calculation of the amplitude reduction through the feed-forward sub-dynamics of the plant. The estimation of biased harmonics (Ahmed et al. (2022)) is summarized in section 3, while its convergence prosperities and parameters tuning are addressed in section 4. A detailed experimental case study of the oscillations compensation with online harmonics estimation is shown in section 5. The conclusions are derived at the end in section 6.

## 2. POWER-BASED OSCILLATIONS CONTROL

The power-based oscillations control (Ruderman (2024b)) is applicable as a plug-in compensator of the oscillatory output quantity  $y(t)$ , see Fig. 1, while the overall plant transfer function  $G(s)$  assumes the double integrator in series at the output channel. The corresponding dominant conjugate-complex pole pair at  $\lambda_{1,2} = \sigma \pm j\omega$  is assumed to be either undamped i.e.  $\sigma = 0$  or very low damped i.e.  $0 \leq \zeta \ll 1$ ;  $\zeta = -\sigma(\sigma^2 + \omega^2)^{-1/2}$  is the standard (normalized) damping ratio. Note that the power-based control is also capable to compensate for even slowly diverging output oscillations, i.e. for  $-1 \ll \zeta < 0$ . This case will be demonstrated in the experimental study where a proportional-integral (PI) feedback controller  $\tilde{u}$ , cf. Fig. 1, forces the otherwise stable  $G(s)$  to have the closed-loop system with a dominant pole pair with  $\sigma > 0$ .

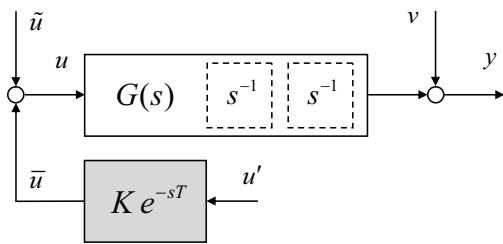


Fig. 1. Discrete power-based control  $u'$  subject to the gain shaping and time-delay synchronization.

It is assumed that the single measured output of the process has the form

$$y(t) = Y_0 + A \sin(\omega t + \phi) + v(t), \quad t \geq 0, \quad (1)$$

where  $y(t), v(t) \in \mathbb{R}$  are the measured signal with the respective bounded noise.  $A > 0$  and  $\omega > 0$  are the amplitude and the frequency of oscillations, correspondingly,  $Y_0 \in \mathbb{R}$  is the bias and  $\phi \in [0, 2\pi)$  is the phase. For the purpose of estimation, we assume that all these parameters are quasi-constant omitting their explicit dependence on time in the notation. Also we note that for the power-based

compensation of the harmonic part in  $y(t)$ , the estimation of the instantaneous triple  $[\hat{Y}_0, \hat{A}, \hat{\omega}](t)$  is assumed, while the phase parameter is not required.

The discrete power-based control, introduced in Ruderman (2024b), is given (for the second-order systems) by

$$u'(t) = k \hat{\omega}^2 \hat{A}(t^*) \quad (2)$$

with

$$\hat{A}(t^*) \equiv \hat{A} \operatorname{sign}(y(t^*) - \hat{Y}_0), \quad (3)$$

where  $t^*$  denotes the time instant of the last extrema, i.e. either minimum or maximum of the oscillating output subtracting the bias, i.e.  $(y(t) - \hat{Y}_0)$ . Recall that the estimate (correspondingly update) of the oscillations parameters  $[\hat{Y}_0, \hat{A}, \hat{\omega}]$  appears twice per period, cf. Ruderman (2024b). As shown in Ruderman (2024b), an optimal gain (over one period of harmonic oscillations) is

$$k = \frac{\sqrt{3}}{2\pi}, \quad (4)$$

that compensates for an undamped oscillation in  $y(t)$ . Moreover, for taking into account the phase lag of the feed-forward sub-dynamics in  $G(s)$ , cf. Fig. 1, it was shown that the corresponding time delay factor

$$T = \left(2\pi + \arg[\tilde{G}(j2\hat{\omega})]\right) \hat{\omega}^{-1} \quad (5)$$

is required. Recall that  $T$  shifts the control value  $u'$  by the negative phase lag with respect to the full period  $2\pi\omega^{-1}$  and, thus, synchronizes the control value  $\bar{u}$  with an internal input to the double integrator inside of  $G(s)$ . Note that some uncertainties due to disturbances and (eventually) feedback propagation at the input of the double-integrator are not taken into account. Thus, only an approximative  $\tilde{G} \approx G(s)s^2$  can be assumed. The overall gain-shaped and time-delay-synchronized control value is then given by

$$\bar{u}(t) = K u'(t - T), \quad (6)$$

cf. Fig. 1, where the gain factor  $K$  must be inverse to the input-output power norm of the gain-reducing sub-dynamics  $\tilde{y}(j\omega) = \tilde{G}(j\omega)u(j\omega)$ . Since the power-based control  $u'$  is the rectangular shaped piecewise constant value  $U$ , the corresponding amplitude reduction is  $|\tilde{G}(s)|U$ . This requires the amplification factor to be

$$1 < K < |\tilde{G}(j\omega)|^{-1}, \quad (7)$$

provided  $\tilde{G}(s)$  has some low-pass transfer characteristics.

A numerically simulated response of the controlled system  $G(s)$ , with the simultaneous use of a destabilizing PI controller  $\tilde{u}$  and the stabilizing power-based control  $\bar{u}$  given by (2),(3),(5),(6) is exemplary shown in Fig. 2 for the sake of a better exposition. Note that the parameters of the system plant and feedback control are the same as the identified, correspondingly assigned, in the provided below experimental case study, cf. section 5. Both boundary values of the gain amplification factor  $K = \{1.4, 4.24\}$  are exemplified, cf. (7), while a lower boundary  $> 1$  had to be assigned for stabilizing the otherwise unstable oscillations of  $y(t)$ , which is driven by the PI feedback  $\tilde{u}$ .

Recall that for implementation of the above control strategy we need to identify online the amplitude of oscillations, the bias and the angular frequency. This is required to be sufficiently fast with regard to a half of the oscillations period (the sampling of the discrete control update).

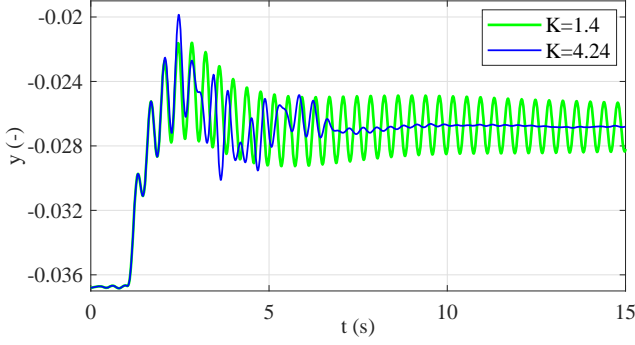


Fig. 2. Simulated response of the stabilized oscillating output for two boundary gain values  $K$ .

### 3. ESTIMATION OF BIASED HARMONIC

Following Ahmed et al. (2022) and Ushirobira and Efimov (2023), we can observe that for (1) with  $v \equiv 0$  the following relation is satisfied:

$$\begin{aligned} y(t-3\tau) - y(t-2\tau) + y(t-\tau) - y(t) \\ = 2 \cos(\omega\tau) (y(t-2\tau) - y(t-\tau)) \end{aligned}$$

for all  $t \geq 0$  and any time delay  $\tau > 0$ . Therefore, the following linear regression equation can be used for estimation of the angular frequency  $\omega$ :

$$\tilde{y}(t) = \tilde{\varphi}(t)\theta_0 + \tilde{v}(t), \quad (8)$$

where

$$\begin{aligned} \tilde{y}(t) &= y(t-3\tau) - y(t-2\tau) + y(t-\tau) - y(t), \\ \tilde{\varphi}(t) &= 2(y(t-2\tau) - y(t-\tau)), \quad \theta_0 = \cos(\omega\tau), \\ \tilde{v}(t) &= 2 \cos(\omega\tau) (v(t-\tau) - v(t-2\tau)) + v(t-3\tau) \\ &\quad - v(t-2\tau) + v(t-\tau) - v(t), \end{aligned}$$

and the new noise  $\tilde{v}$  is also bounded. Different algorithms can be used to estimate the parameter  $\theta_0$ . In particular, the conventional gradient descent method can be applied:

$$\dot{\hat{\theta}}_0(t) = \gamma_1 \tilde{\varphi}(t) (\tilde{y}(t) - \tilde{\varphi}(t)\hat{\theta}_0(t)) \quad (9)$$

or its finite-time converging version Wang et al. (2020b):

$$\dot{\hat{\theta}}_0(t) = \gamma_1 \tilde{\varphi}(t) \sqrt{|\tilde{y}(t) - \tilde{\varphi}(t)\hat{\theta}_0(t)|} \text{sign}(\tilde{y}(t) - \tilde{\varphi}(t)\hat{\theta}_0(t)). \quad (10)$$

With an adaptation gain  $\gamma_1 > 0$ , then

$$\hat{\omega}(t) = \tau^{-1} \arccos(\hat{\theta}_0(t))$$

can be chosen as the estimate of the angular frequency.

Knowing the angular frequency, the problem of estimation of the bias  $Y_0$ , the amplitude  $A$  (and the phase  $\phi$ ) can be also formulated in the linear regression form:

$$\begin{aligned} y(t) &= \varphi^\top(t)\theta + v(t) \\ &= \hat{\varphi}^\top(t)\theta + \hat{v}(t), \end{aligned}$$

for

$$\begin{aligned} \varphi^\top(t) &= [1 \quad \sin(\omega t) \quad \cos(\omega t)], \\ \theta^\top &= [Y_0 \quad A \cos(\phi) \quad A \sin(\phi)], \\ \hat{\varphi}^\top(t) &= [1 \quad \sin(\hat{\omega}(t)t) \quad \cos(\hat{\omega}(t)t)], \\ \hat{v}(t) &= v(t) + (\varphi(t) - \hat{\varphi}(t))^\top \theta. \end{aligned}$$

Then, a similar gradient descent algorithm can be utilized to estimate  $\theta$ :

$$\dot{\hat{\theta}}(t) = \gamma_2 \hat{\varphi}(t)(y(t) - \hat{\varphi}(t)\hat{\theta}(t)) \quad (11)$$

for  $\gamma_2 > 0$ , where

$$\begin{aligned} \hat{Y}_0(t) &= \hat{\theta}_1(t), \quad \hat{A}(t) = \sqrt{\hat{\theta}_2^2(t) + \hat{\theta}_3^2(t)}, \\ \hat{\phi}(t) &= \arctan\left(\frac{\hat{\theta}_3(t)}{\hat{\theta}_2(t)}\right) \end{aligned}$$

are the estimates of the remaining parameters in (1).

In this case  $\tau$ ,  $\gamma_1$  and  $\gamma_2$  are the estimation algorithm parameters that have to be properly tuned.

## 4. CONVERGENCE PROPERTIES AND PARAMETERS TUNING

The gradient descent algorithms (9) or (11) guarantee convergence of the parameter estimates to their ideal values in the noise-free setting if the regressors ( $\tilde{\varphi}(t)$  or  $\hat{\varphi}(t)$  in (9) or (11), respectively) are persistently excited, cf. e.g. Sastry and Bodson (1989); Efimov and Fradkov (2015). Recall that a bounded signal  $\hat{\varphi}(t)$  is called persistently excited Morgan and Narendra (1977) if there exist  $T^* > 0$  and  $\alpha > 0$  such that

$$\int_t^{t+T^*} \hat{\varphi}(s)\hat{\varphi}^\top(s)ds \geq \alpha I$$

for all  $t \geq 0$ , where  $I$  is the identity matrix of an appropriate dimension. For the finite-time converging algorithm (10), an interval excitation can be enough in such a case Wang et al. (2020b), i.e., the above integral property is verified for some  $t \geq 0$ . In the presence of measurement noises, all these algorithms ensure input-to-state stability of the parameter identification errors with respect to the measurement perturbations under persistence of excitation Wang et al. (2020b). The latter property in the absence of noise can be easily verified for  $\tilde{\varphi}(t)$ :

$$\begin{aligned} \tilde{\varphi}(t) &= 2A (\sin(\omega t - 2\omega\tau + \phi) - \sin(\omega t - \omega\tau + \phi)) \\ &= -4A \sin\left(\frac{\omega}{2}\tau\right) \cos\left(\omega t - \frac{3\omega}{2}\tau + \phi\right), \end{aligned}$$

then for  $T^* = \frac{2\pi}{\omega}$

$$\begin{aligned} \int_t^{t+T^*} \tilde{\varphi}^2(s)ds &= 16A^2 \sin^2\left(\frac{\omega}{2}\tau\right) \int_t^{t+T^*} \cos^2\left(\omega s - \frac{3\omega}{2}\tau + \phi\right)ds \\ &= 16A^2 \frac{\pi}{\omega} \sin^2\left(\frac{\omega}{2}\tau\right), \end{aligned}$$

and the excitation is maximal for

$$\tau = \frac{\pi}{\omega},$$

which provides indication for the choice of  $\tau$ . For example, if  $\underline{\omega} \leq \omega \leq \bar{\omega}$  for some known constants  $\bar{\omega}, \underline{\omega}$ , then

$$\frac{\pi}{\bar{\omega}} \leq \tau \leq \frac{\pi}{\underline{\omega}}$$

is a recommended interval. Similarly, performing straightforward calculations, the persistence of the excitation of  $\varphi(t)$  can be checked. We may assume that if the signal-noise ratio in (1) is reasonable, then the same conclusions keep their meaning for the noisy scenario also. It is worth, however, to highlight that the value of  $\tau$  has to be also chosen to provide a sufficient distinguishability between the values  $y(t)$ ,  $y(t-\tau)$ ,  $y(t-2\tau)$  and  $y(t-3\tau)$  in comparison to the noise, i.e., for values of  $\tau$  sufficiently small, the useful part of the signal,  $\sin(\omega t + \phi)$ , stays approximately

the same, while the noise may vary arbitrary in its limits, hence, impacting strongly the identification.

For tuning the adaptation gains  $\gamma_1, \gamma_2$ , we may recall the estimates obtained in Efimov and Fradkov (2015), which indicate that depending on the excitation level, there exist their optimal values providing the best convergence rates and sensitivity to the noise. However, the excitation level may be difficult to determine before the experiment.

The performance of the convergence can be improved using the Dynamic Regressor Extension and Mixing method (Aranovskiy et al. (2017)), which allows the monotone convergence of identification errors with regulated rate of convergence at the price of introduction of additional filters. This method can also be used for finite-time estimation of the parameters vector  $\theta$ , improving the quality of identification with respect to the algorithm (11) but demanding, however, an additional computational effort.

## 5. EXPERIMENTAL CASE STUDY

### 5.1 Mechanical oscillatory setup

The experimental control evaluation is accomplished on the actuated mechanical setup (Ruderman (2022)) with the free hanging oscillatory load, see Fig. 3. The vertical

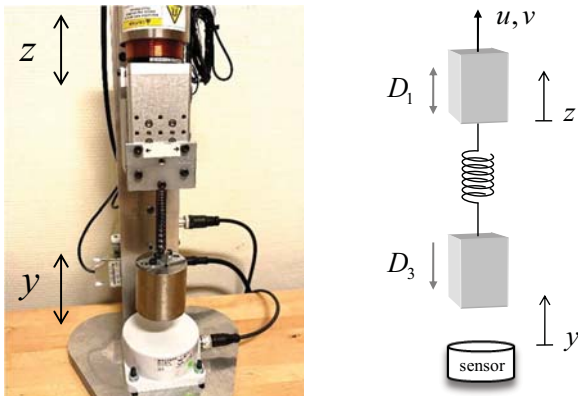


Fig. 3. Experimental oscillatory setup: laboratory view (left) and equivalent mechanical scheme (right).

motion with a constrained degree of freedom  $z \in [0, 0.021]$  m is induced by the voice-coil-based linear actuator which receives the control values  $u \in [0, 10]$  V. Both moving masses are connected via an elastic spring which has the relatively high stiffness but, at the same time, is subject to hardening effects and uncertainties. The load relative displacement  $y(t)$  is the output value of interest and it is measured contact-less by an inductive sensor located below. Despite an axial alignment of both degrees of freedom  $z$  and  $y$  in series, cf. Fig. 3 (right), the latter is subject to an additional process noise. Recall that the free hanging load is without any bearing and, thus, can undergo additional degrees of freedom, even though marginal. A real-time board provides the control and load displacement signals with the sampling rate of  $f_s = 2$  kHz. More details on the system dynamics and parameters can be found in e.g. Ruderman (2023).

The known system model structure and nominal (also partially identified) parameters are given by

$$\nu(s) = H(s) u(s) = \frac{3.2811}{0.0012s + 1} u(s), \quad (12)$$

$$\dot{x}(t) = Ax(t) + B\nu(t) + D, \quad (13)$$

$$y(t) = Cx(t),$$

with the state vector  $x = (\dot{z}, z, \dot{y}, y)^\top$  and

$$A = \begin{pmatrix} -333.35 & -333.33 & 0.015 & 333.33 \\ 1 & 0 & 0 & 0 \\ 0.012 & 266.66 & -0.012 & -266.66 \\ 0 & 0 & 1 & 0 \end{pmatrix}, \quad (14)$$

$$B = (1.667, 0, 0, 0)^\top, \quad C = (0, 0, 0, 1), \quad \text{and}$$

$$D = (-9.806 + 0.83 \text{sign}(\dot{x}_1), 0, -9.806, 0)^\top.$$

When compensating for the constant disturbance terms in  $D$  (see Fig. 3 on the right), which are mainly due to the gravity force, and neglecting the remaining Coulomb friction disturbance of the actuator, the overall input-to-output transfer function of the system is given by

$$G(s) = y(s)u(s)^{-1} = C(sI - A)^{-1}BH(s), \quad (15)$$

where  $I$  is the  $4 \times 4$  identity matrix, cf. Fig. 1.

### 5.2 Unstable PI feedback control

The output displacement  $y(t)$  of the oscillatory passive load is first controlled by a simple PI (proportional-integral) feedback regulator

$$\tilde{u}(t) = 140(R_1 - y(t)) + 170 \int (R_1 - y(t))dt + R_2. \quad (16)$$

It is expected that the PI feedback control alone can neither suppress the undesired output oscillations nor ensure the stability of the closed control loop, considering that the loop transfer function is of the fifth order. However, an integral control action is still necessary for regulation towards the reference value  $R_1$ , since multiple system uncertainties can not be captured by the nominal plant model, like e.g. uncertainties of the mechanical friction or force ripples of the voice-coil-motor. On the contrary, the known total gravity force (induced by both the actuator and the load masses) is feed-forward compensated by the constant  $R_2$ , cf. (16). The measured unstable output response of the load position is shown in Fig. 4.

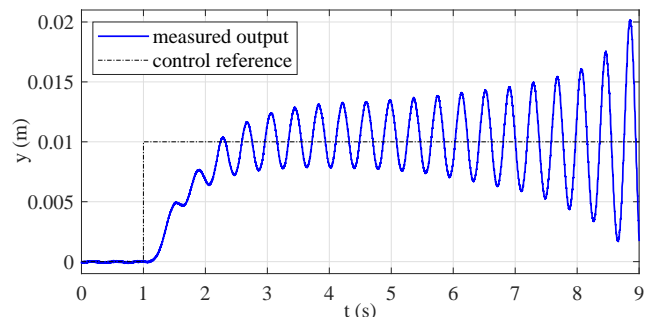


Fig. 4. Unstable load position response of PI-control.

The parameters estimate is performed simultaneously on the measured (diverging) oscillatory output signal. The tuned parameters of the estimation algorithm (cf. sections 3, 4) are  $\tau = 0.075$  sec, and  $\gamma_1 = 1.5 \times 10^5$ ,  $\gamma_2 = 10^6$ .

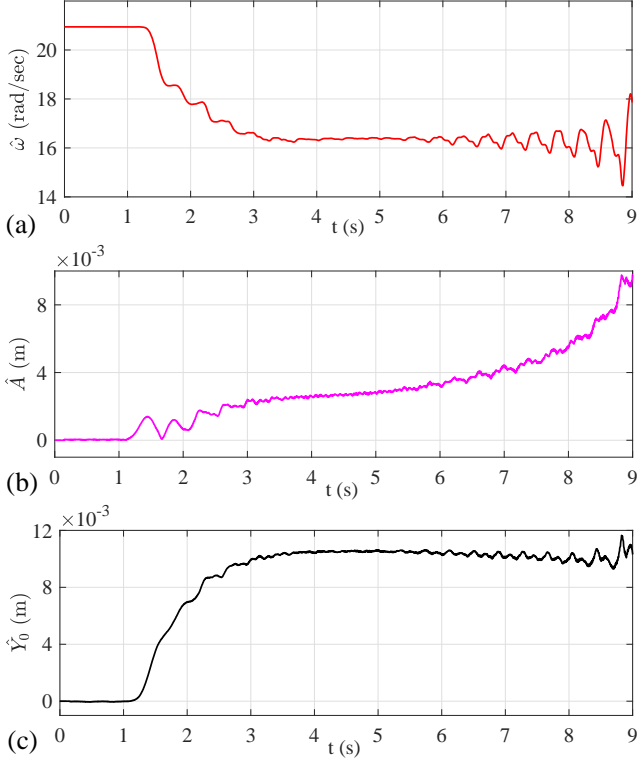


Fig. 5. Online estimation of harmonic parameters at unstable response: frequency (a), bias (b), amplitude (c).

The online parameters estimation over time is shown for  $\hat{\omega}$ ,  $\hat{A}$ , and  $\hat{Y}_0$  in Fig. 5 (a), (b), and (c), respectively. One can recognize that once the  $y(t)$  signal starts to diverge faster (at time about  $t > 8$  sec, cf. Fig. 4), the parameters estimate loses the convergence, in particular visible for  $\hat{\omega}(t)$ . That case, the parameters estimate becomes inappropriate for a power-based control and can, in the worst case, even accelerate destabilization of the output. It seems logical that for an effective use of the online parameters estimation in combination with the power-based control, both the convergence of the estimate and the suppression of oscillations should occur within a few periods.

### 5.3 Unstable PI feedback control with power-based control

Next, the power-based control (6) with (5), (2) and (3) is switched on at time  $t = 2.5$  sec, thus augmenting the otherwise unstable PI regulator (16), cf. Fig. 1. The set parameters of the estimation algorithm are the same as above, cf. section 5.2. The determined feed-forward plant sub-dynamics (based on the identified model) is

$$\tilde{G}(s) = \frac{0.1544s + 3432}{0.002824s^3 + 3.295s^2 + 785.5s + 784.5}, \quad (17)$$

that results in the gain upper bound, cf. (7),

$$|\tilde{G}(j\omega)|^{-1} = 4.24.$$

The properly tuned gain, assigned in the real-time control experiments, is  $K = 2.4$ . The measured load position response, stabilized by the power-based control is shown in Fig. 6. Also here, the online parameters estimation over the time are shown for the sake of completeness in Fig. 7, for  $\hat{\omega}$ ,  $\hat{A}$ , and  $\hat{Y}_0$  in (a), (b), and (c), respectively.

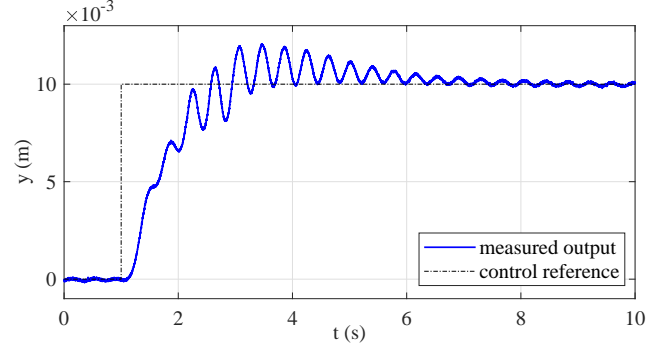


Fig. 6. Stabilized load position response of PI-control augmented by power-based control at  $t = 2.5$  sec.

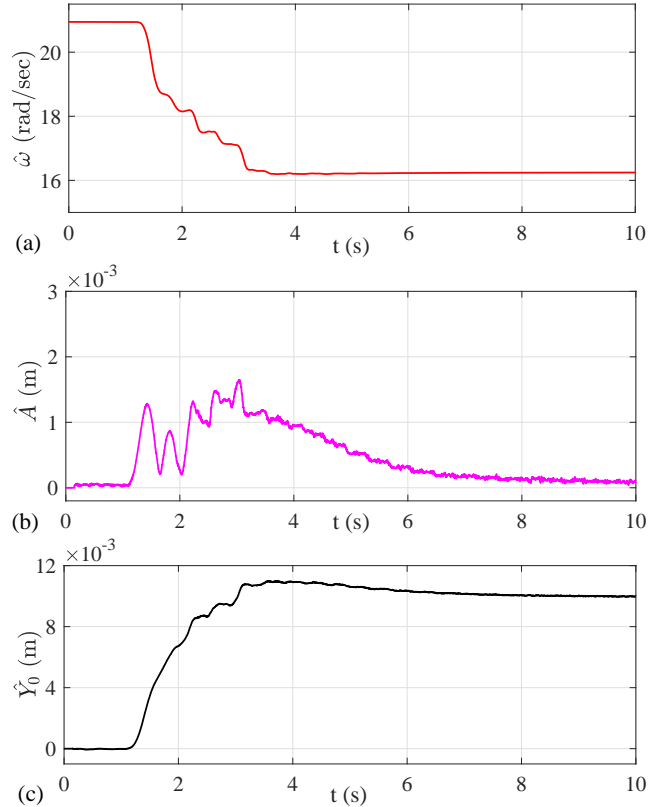


Fig. 7. Online estimation of harmonic parameters at stable response: frequency (a), bias (b), amplitude (c).

## 6. CONCLUSIONS

Pursuing the goal of reduction of the communication efforts within a control loop, particularly when compensating for marginally damped or slowly diverging output oscillations with non-collocated actuation and load sensing, a new method called discrete power-based control was recently introduced in Ruderman (2024b). The control commutates twice per oscillations period and for its effective application, the power-based compensation scheme necessitates the knowledge of several key parameters, as the instantaneous angular frequency, the amplitude, and the bias of the harmonic signal. These have to be reliable and rapidly estimated online. This paper extended the capabilities of the power-based control by incorporating a finite-time estimation of the required parameters, fol-

lowing the ideas of Wang et al. (2020b); Ahmed et al. (2022). In addition, an improved analytic calculation of the impulse weighting factor was proposed, enhancing the control's effectiveness. The power-based oscillation control with online estimation of the harmonic parameters was experimentally evaluated. The tests were conducted on a fifth-order actuator system with a free-hanging load subjected to gravity and measurement noise. The evaluation provided insights into the applicability and performance of the control method in practical scenarios.

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