

Obtaining Consistent Parameter Estimators for Second-Order Modulus Models

Fredrik Ljungberg and Martin Enqvist

Introduction

This work deals with the issue of obtaining consistent parameter estimators in nonlinear regression models where the regressors are second-order modulus functions, which is a structure that is often used in models of marine vessels. It is shown that the accuracy of an instrumental variable estimator can be improved by conducting experiments where the **input signal has a static offset** of sufficient amplitude and the **instruments are forced to have zero mean**.

Taylor alternative

Abkowitz (1964):
Taylor-series expansion

$$\begin{aligned} \tau_j(\xi) &= \tau_j(\xi_0) + \sum_{i=1}^{2n_{act}} \left(\frac{\partial \tau_j(\xi)}{\partial \xi_i} \right)_{\xi_0} \Delta_{\xi_i} + \\ &\quad \frac{1}{2} \frac{\partial^2 \tau_j(\xi)}{(\partial \xi_i)^2} \Big|_{\xi_0} \Delta_{\xi_i}^2 + \frac{1}{6} \frac{\partial^3 \tau_j(\xi)}{(\partial \xi_i)^3} \Big|_{\xi_0} \Delta_{\xi_i}^3 \\ j &= 1, \dots, n_v \end{aligned}$$

Port/starboard symmetry

⇒ no second-order terms.

Fedyaevsky and Sobolev (1963):
Second-order modulus functions

$$\begin{aligned} (m - X_{\dot{u}})\dot{u} &= X_{|u|u}|u|u + (1-t)T + (m + X_{vr})vr \\ &\quad + X_{\delta}\delta^2 + X_{ext} \\ (m - Y_{\dot{v}})\dot{v} &= -(m - Y_{ur})ur \\ &\quad + Y_{uv}uv + Y_{|v|v}|v|v + Y_{|v|r}|v|r + Y_{\delta}\delta + Y_{ext} \\ (mX_G - N_{\dot{v}})\dot{v} &+ (I_z - N_r)\dot{r} = -(mx_G - N_{ur})ur \\ &\quad + N_{uv}uv + N_{|v|v}|v|v + N_{|v|r}|v|r + N_{\delta}\delta + N_{ext} \end{aligned}$$

Port/starboard symmetry thanks to modulus operator.

Motivating example

System: $\begin{cases} x(k+1) = n_0x(k)|x(k)| + f_0u(k) + w(k) \\ y(k) = x(k) + e(k) \end{cases}$

Model: $\hat{y}(k|\theta) = ny(k-1)|y(k-1)| + fu(k-1)$

Zero-centered input ($u(k) = \tilde{u}(k)$, $\bar{E}\{\tilde{u}(k)\} = 0$)

Asymptotic LS estimate: $\lim_{N \rightarrow \infty} \hat{\theta}_N^{LS} = \dots = \begin{bmatrix} \frac{n_0 \bar{E}\{x|x|(x+e)|x+e|\}}{\bar{E}\{x^4+6x^2e^2+e^4\}} \\ f_0 \end{bmatrix} \neq \begin{bmatrix} n_0 \\ f_0 \end{bmatrix}$

Pick noise-free regressors as instruments

$$\zeta(k) = [x(k-1)|x(k-1)| u(k-1)]^T$$

$$\text{Asymptotic IV estimate: } \lim_{N \rightarrow \infty} \hat{\theta}_N^{IV} = \dots = \begin{bmatrix} \frac{n_0 \bar{E}\{x^4\}}{\bar{E}\{x|x|(x+e)|x+e|\}} \\ f_0 \end{bmatrix} \neq \begin{bmatrix} n_0 \\ f_0 \end{bmatrix}$$

Excitation offset ($u(k) = \bar{u} + \tilde{u}(k)$, $\bar{E}\{\tilde{u}(k)\} = 0$)

Subtract mean from instruments

$$\zeta(k) = [x(k-1)^2 - \bar{E}\{x(k-1)^2\} u(k-1) - \bar{E}\{u(k-1)\}]^T$$

$$\text{Asymptotic IV estimate: } \lim_{N \rightarrow \infty} \hat{\theta}_N^{IV} = \dots = \begin{bmatrix} n_0 \\ f_0 \end{bmatrix}$$

Lemma: Consistency

System: $\begin{cases} x(k+1) = \Phi^T([x^T(k) \ u^T(k)]^T) \theta_0 + w(k) \\ y(k) = x(k) + e(k) \end{cases}$

Model: $\hat{y}(k) = \Phi^T([y^T(k-1) \ u^T(k)]^T) \theta$

Common assumptions:

- $f = \Phi^T(\cdot)\theta$ sec.-ord. mod.
- w, e zero mean and *i.i.d.*
- Global identifiability
- Open-loop experiments
- ζ, w, e mutually indep.
- $E\{\zeta(k)\Phi^T(k)\}$ full rank

Key assumptions:

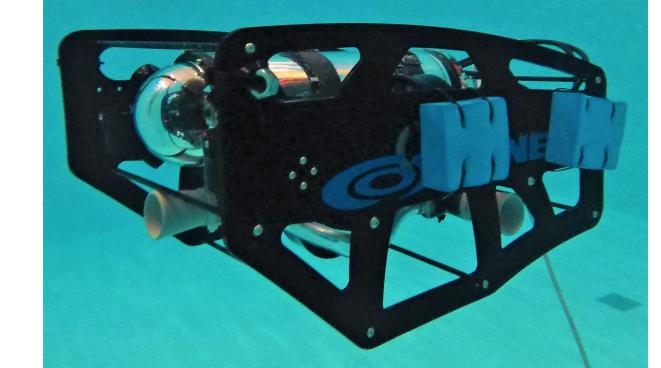
- The input excites the system so that $|x_i(k)| > \eta_i > |e_i(k)|$, $i = 1, \dots, n$
- $\bar{E}\{\zeta(k)\} = 0$

⇒ IV consistent estimator of θ .

Yaw-rate simulation

$$\begin{aligned} r(k+1) &= a_0r(k) + n_0r(k)|r(k)| + f_0\tau(k) + w(k), \\ y(k) &= r(k) + e(k), \end{aligned}$$

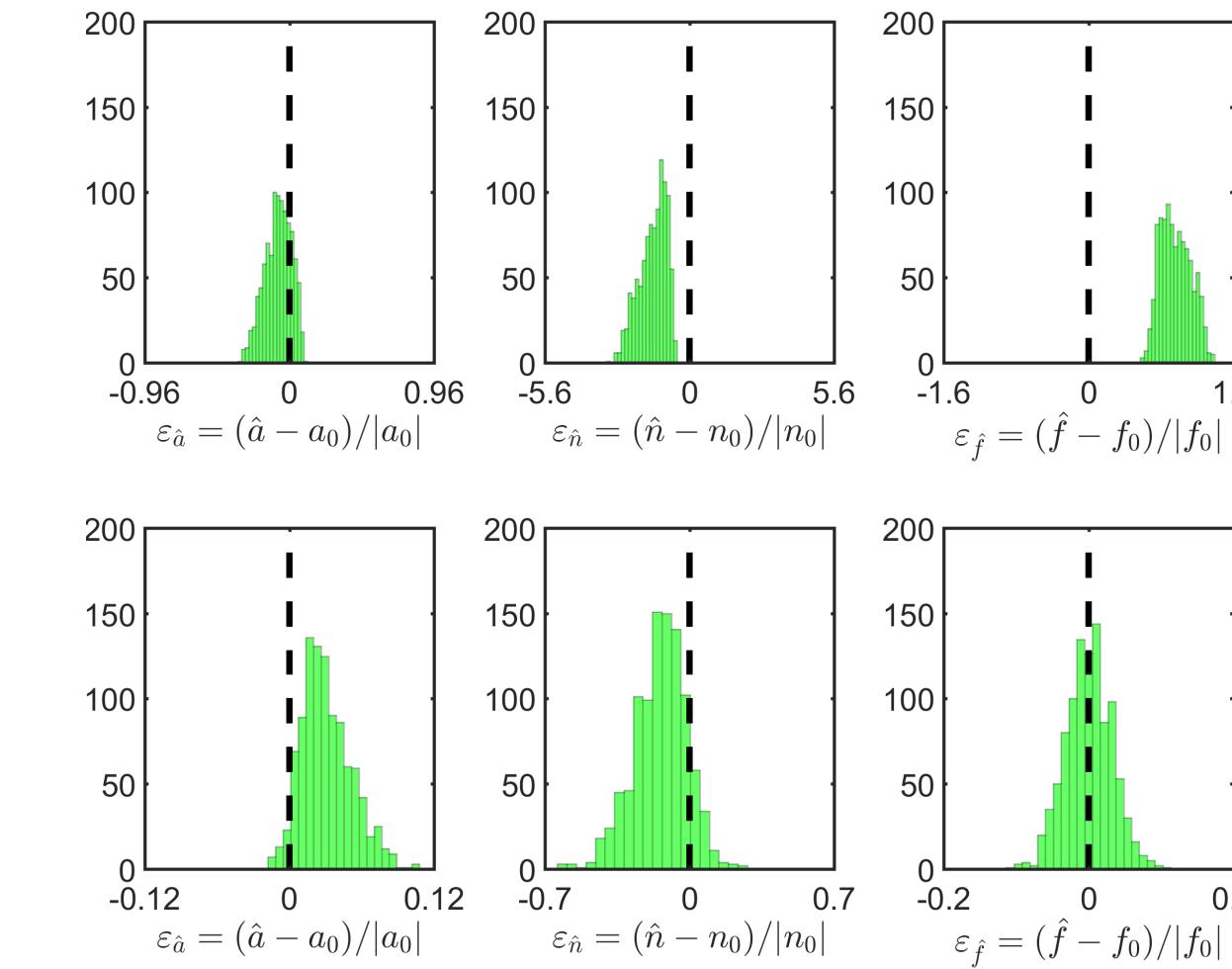
The model is describing the yaw motion of an underwater vehicle (Fossen 2011).



$\hat{\theta} - \theta_0$ histograms

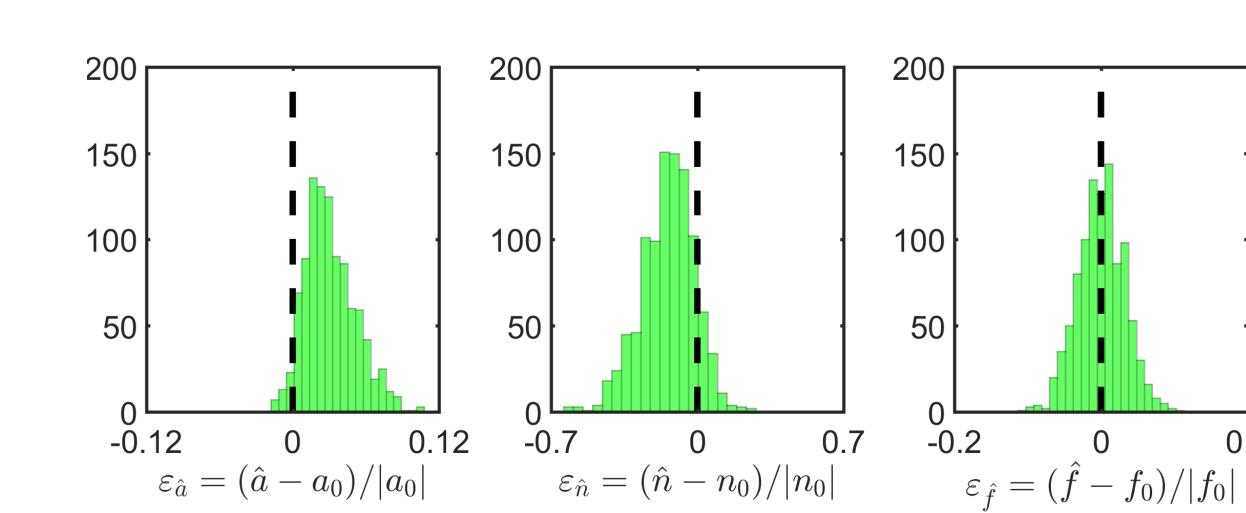
(zero-centered input)

LS



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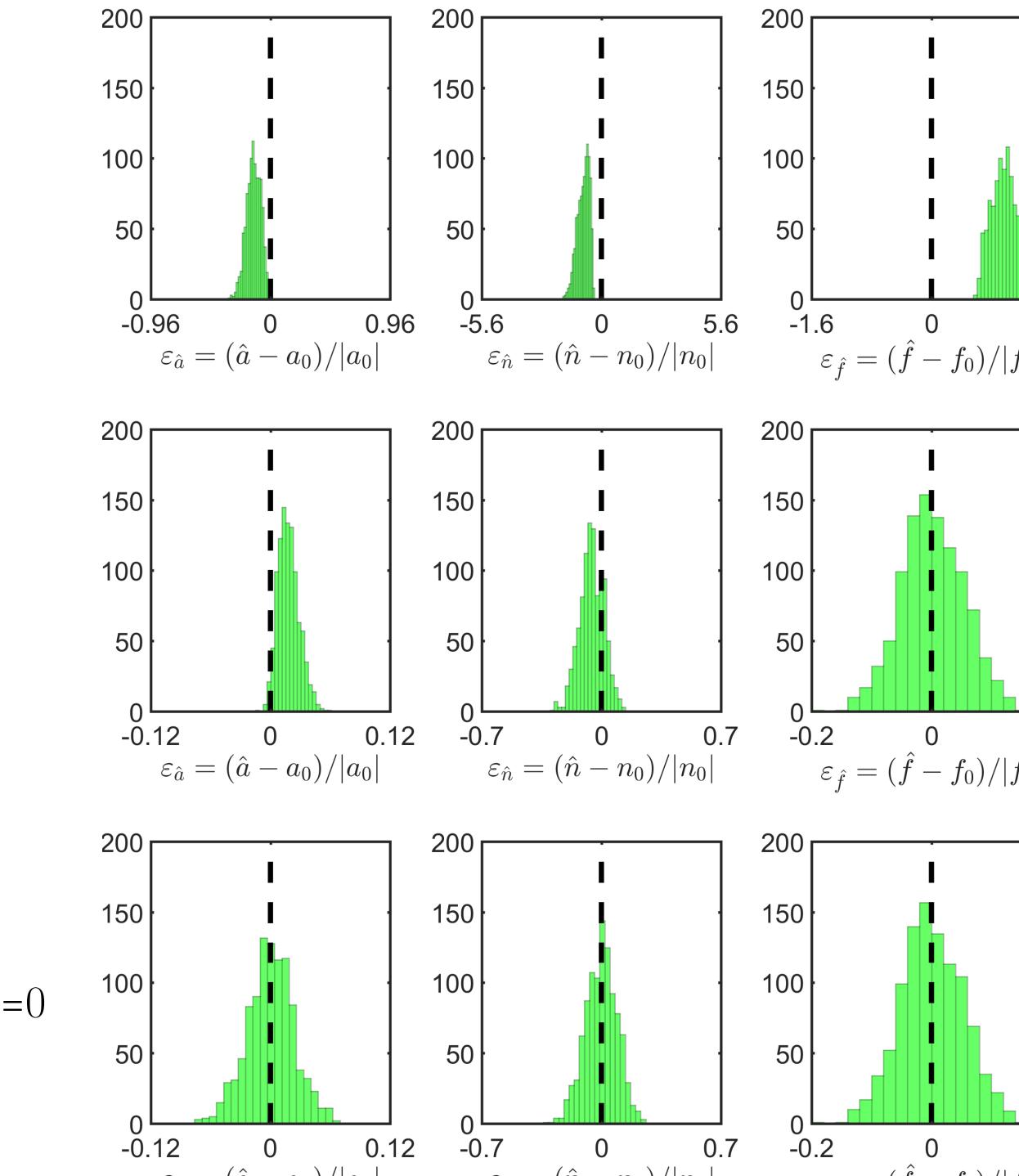
IV



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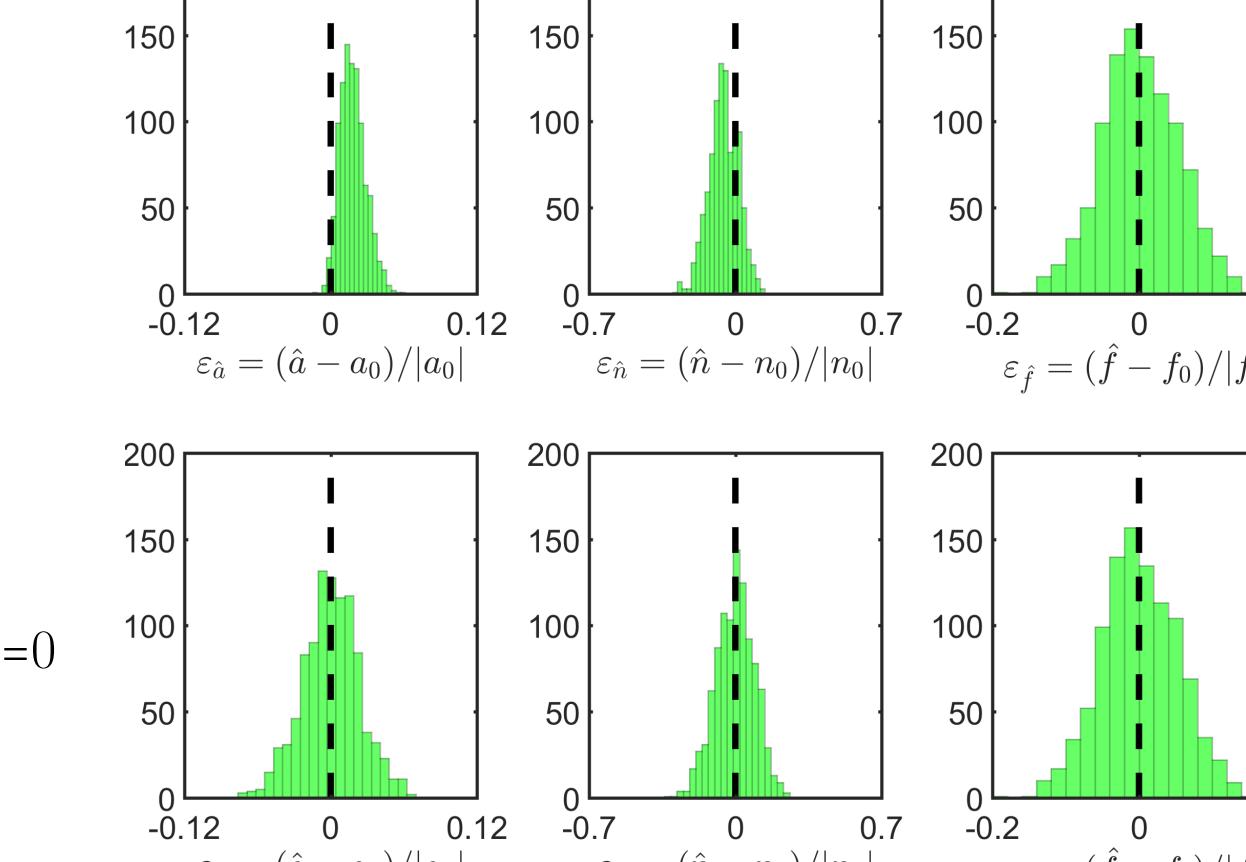
$\hat{\theta} - \theta_0$ histograms
(excitation offset)

LS



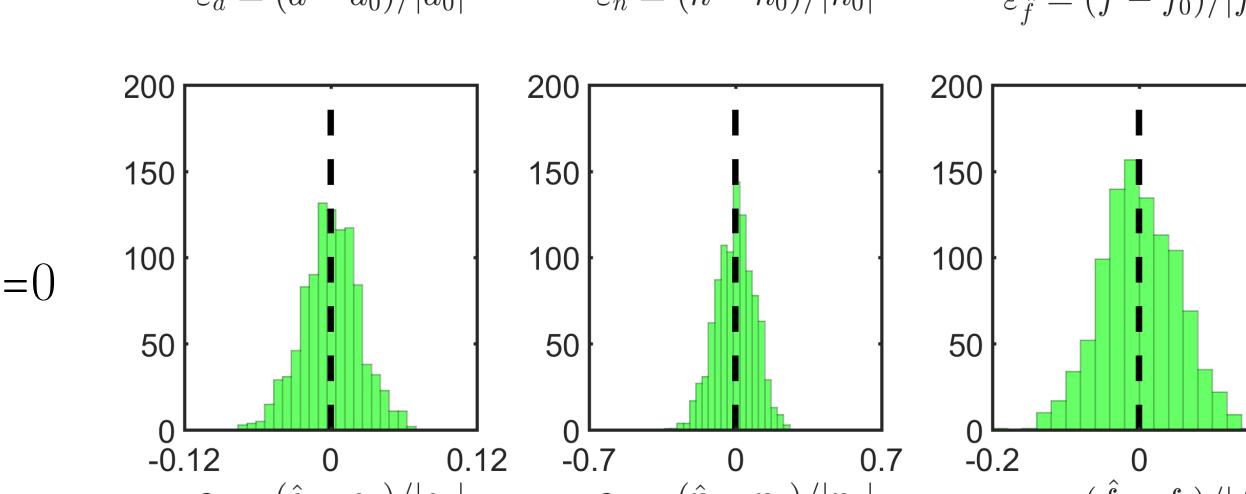
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IV



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IV $E\{\zeta\}=0$



👍

Surface-vessel simulation

6-DOF system (surge, sway, heave, roll, pitch, yaw):

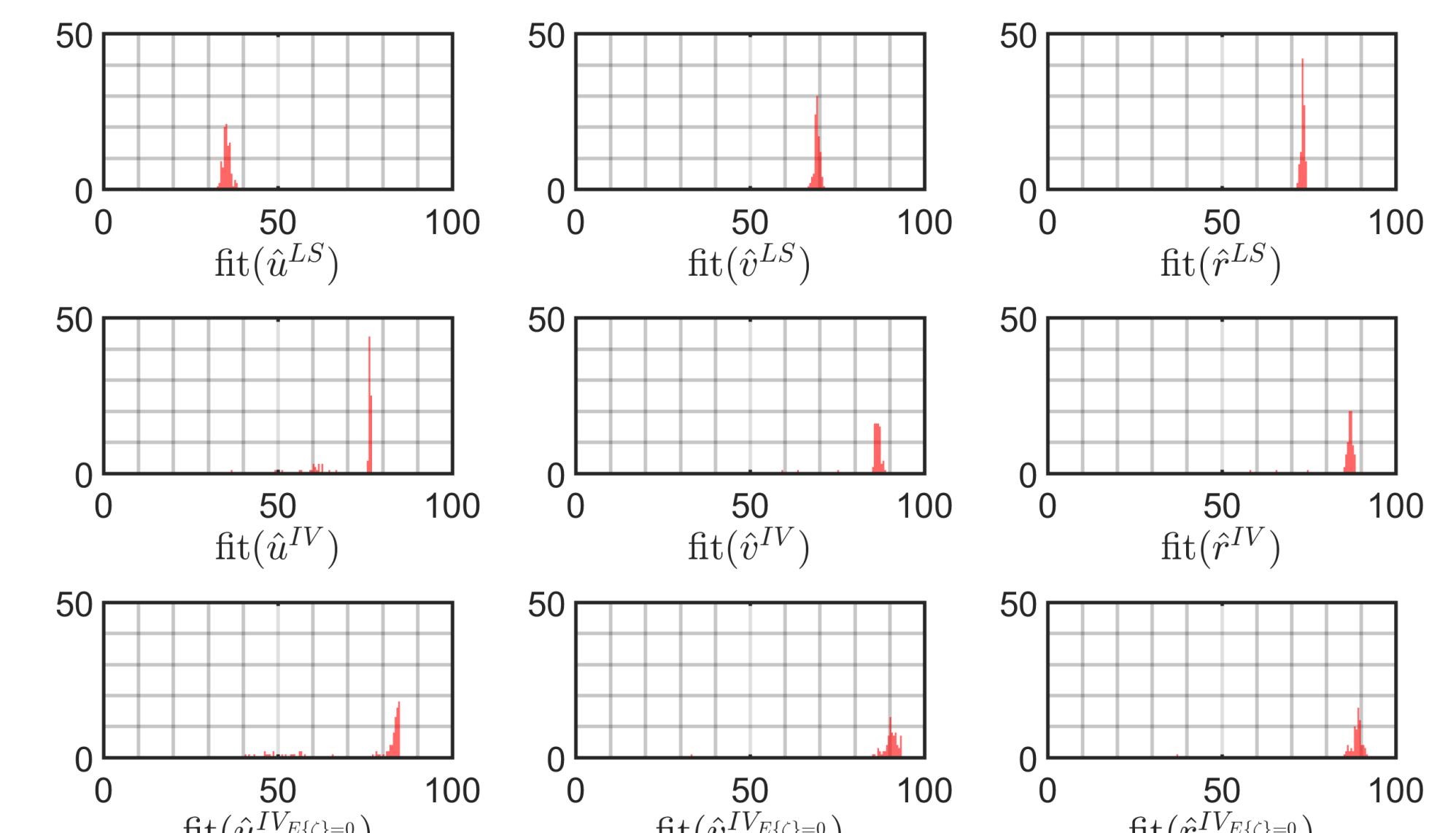
$$\begin{aligned} M\dot{\nu} + C_{RB}\nu + N(\nu)\nu &= \tau_{act} + \tau_{wind} + \tau_{wave} \\ y &= H\nu + e, \end{aligned}$$



3-DOF second-order modulus model (surge, sway, yaw):

$$y(k+1) = \Phi^T([y^T(k) \ \tau_{act}^T(k)]^T) \theta, \quad \theta \in \mathbb{R}^{17}$$

Fit histograms
(excitation offset)



Possible future work and ideas

- A more thorough investigation of usefulness of the proposed method for limited data sets.
- Consider the case where only parts of the state vector can be measured directly.
- Understand how to deal with cubic terms (Abkowitz' model structure).