Ship Modelling for Estimation and Control

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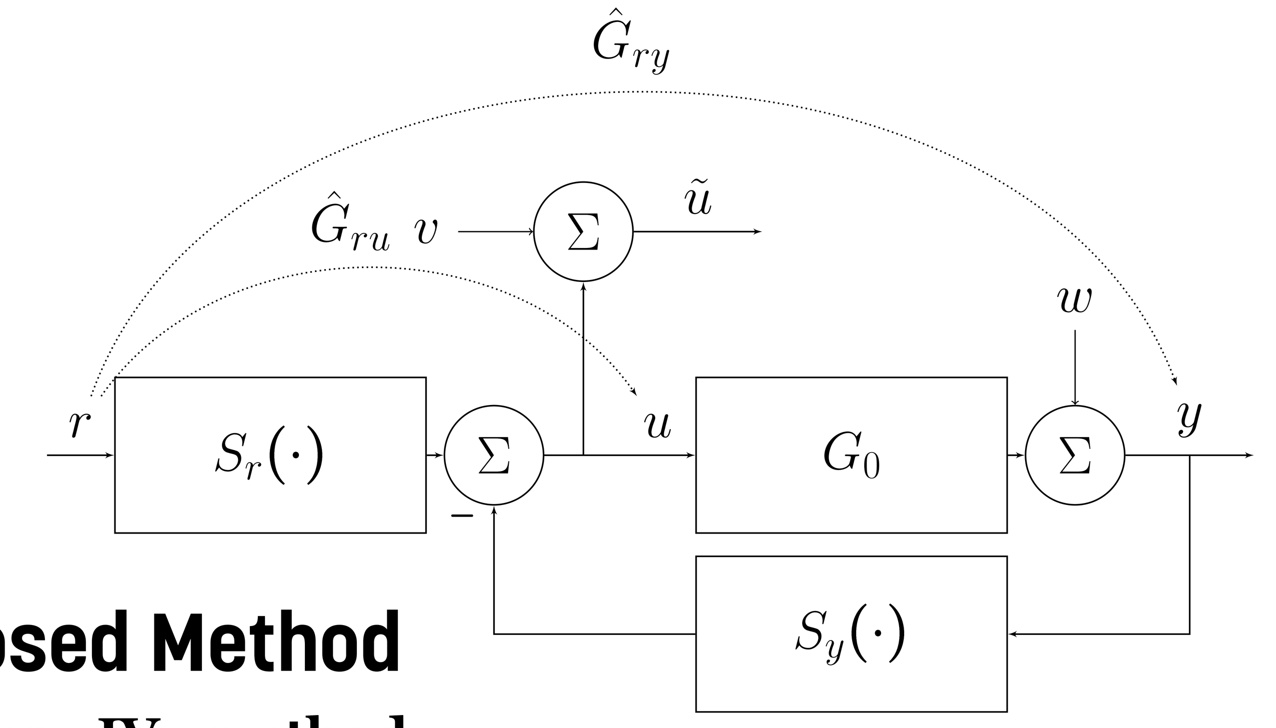
Introduction

Many mechanical systems have time-dependent physical properties and a marine vessel is one example of such a system. By estimating these properties online, a higher model accuracy can be obtained. For online estimation only a limited set of sensors are available and therefore estimation of a complete model can be cumbersome. One alternative is to look at the system as a **dynamic network** and model a part of it. In that case the estimation problem can sometimes be turned into a closed-loop errors-in-variables formulation.

IV Estimation for Closed-loop Systems

$$\hat{\theta}_{IV} = \text{argmin}_{\theta} \frac{1}{N}\sum_{t=1}^{N} \left\| \zeta(t)L(q)\varphi^T(t)\,\theta - \zeta(t)L(q)y(t) \right\|_W^2 \qquad (1)$$

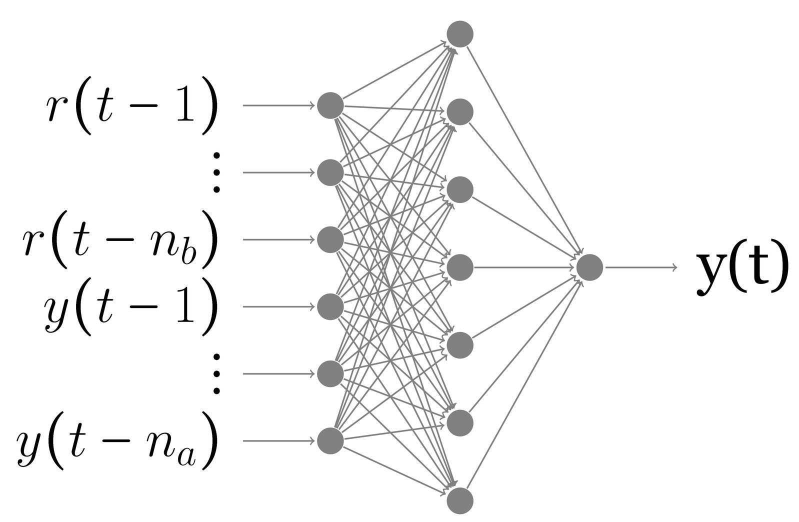
- Challenge: Correlation between input and noise
- Solution: Two-step method using models of closed-loop relations



Proposed Method

Two-step IV method with artificial neural networks

1. Estimate two artificial neural networks which relates $r(t)$ to $y(t)$ and $u(t)$, respectively. Use the neural networks to simulate noise-free versions of $y(t)$ and $u(t)$, denoted $\hat{\hat{y}}(t)$ and $\hat{\hat{u}}(t)$.
2. Form the instrument vector to mimic a noise-free version of the regression vector and estimate the sought after parameters using (1).



$$\zeta_f(t) = L(q)\begin{bmatrix} \hat{\hat{y}}(t-1) \\ \vdots \\ \hat{\hat{y}}(t-n_a) \\ \hat{\hat{u}}(t-1) \\ \vdots \\ \hat{\hat{u}}(t-n_b) \end{bmatrix}^T$$

Simulation Results

- True system: $G_0 = \frac{b_1 q^{-1} + b_2 q^{-2}}{1 + f_1 q^{-1} + f_2 q^{-2}}$
- Evaluation metric: $\text{fit}(\mathbf{y}, \hat{\mathbf{y}}) = 100(1 - \frac{\|\mathbf{y}-\hat{\mathbf{y}}\|}{\|\mathbf{y}-\frac{1}{N}\sum_{i=1}^{N} y_i\|})$
- Result illustration: Fit-histograms from Monte Carlo simulations

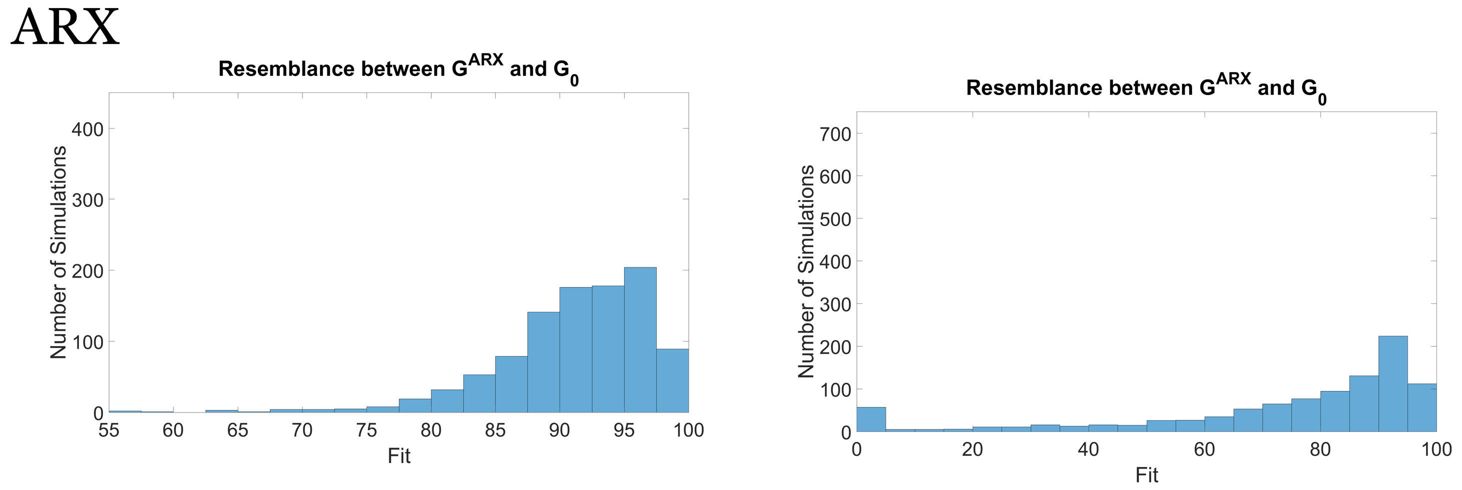
Set-up 1

$$u = \begin{cases} r - y & \text{if } (r-y) \geq 0 \\ 0.1(r-y) & \text{if } (r-y) < 0 \end{cases}$$

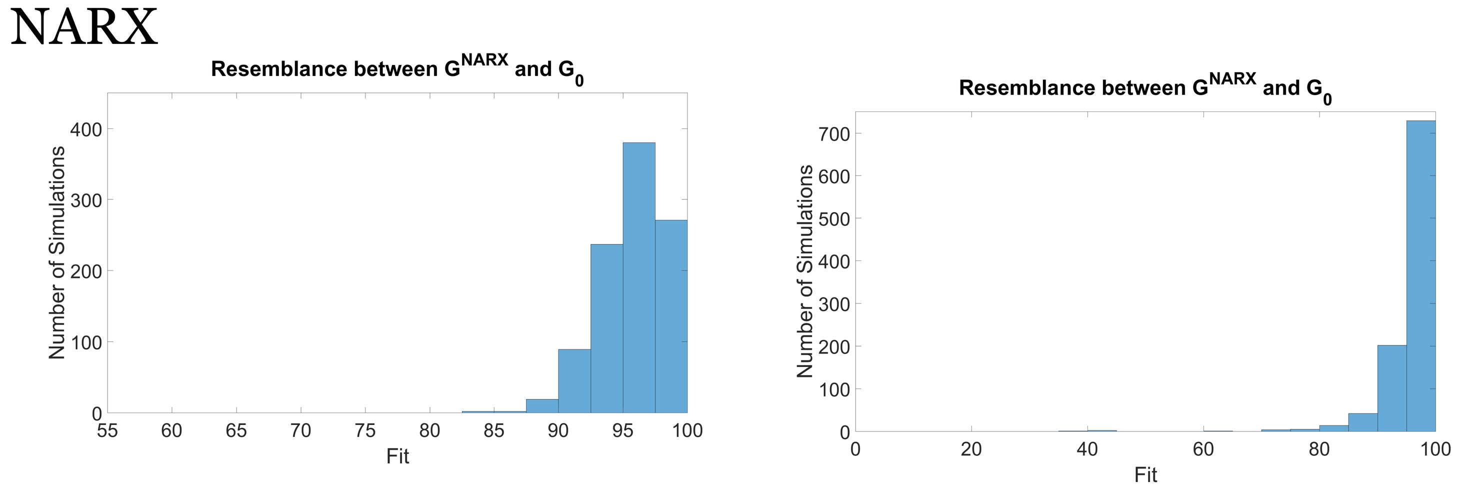
Set-up 2

$$e = 0.01r + r^2 - y,$$
$$u = \text{sat}(F_{PI}(e)).$$

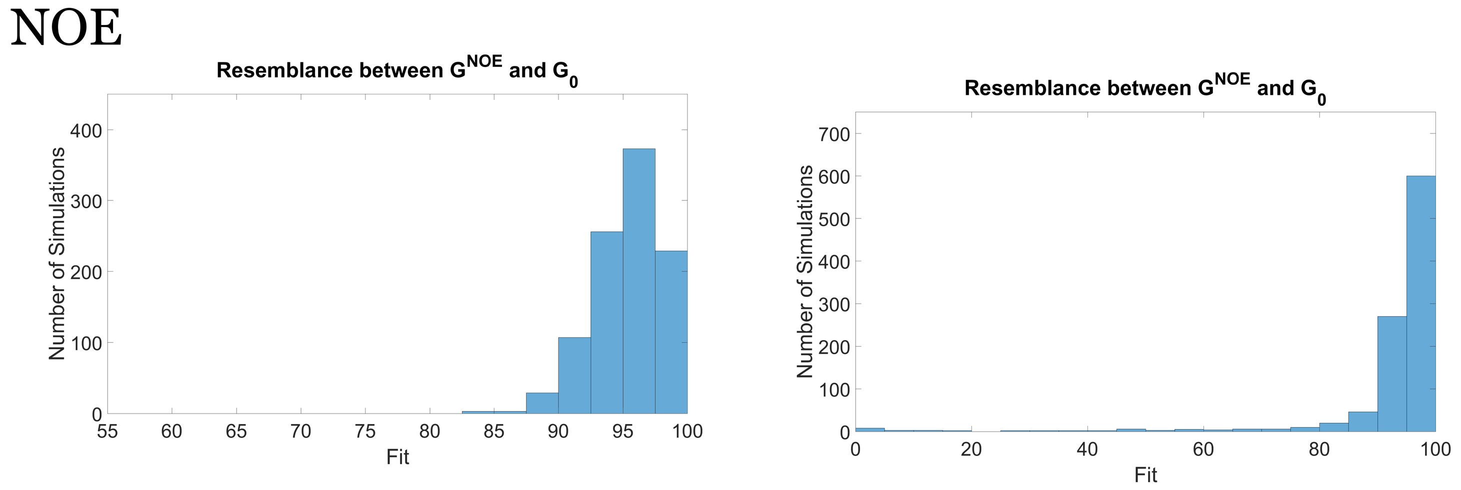
ARX



NARX



NOE



NARX or NOE

Set-up 1

Estimation data

$\text{fit}(u, \hat{u}^{NARX})$ = 21.6 ± 1.1
$\text{fit}(u, \hat{u}^{NOE})$ = 20.8 ± 19.2
$\text{fit}(y, \hat{y}^{NARX})$ = 14.8 ± 1.0
$\text{fit}(y, \hat{y}^{NOE})$ = 15.5 ± 38.1

Noise-free estimation data

$\text{fit}(u, \hat{u}^{NARX})$ = 77.7 ± 2.0
$\text{fit}(u, \hat{u}^{NOE})$ = 73.3 ± 6.3
$\text{fit}(y, \hat{y}^{NARX})$ = 76.2 ± 2.1
$\text{fit}(y, \hat{y}^{NOE})$ = 64.6 ± 9.6

Set-up 2

Estimation data

$\text{fit}(u, \hat{u}^{NARX})$ = 19.9 ± 10.5
$\text{fit}(u, \hat{u}^{NOE})$ = 47.4 ± 12.0
$\text{fit}(y, \hat{y}^{NARX})$ = 26.1 ± 7.9
$\text{fit}(y, \hat{y}^{NOE})$ = 43.0 ± 16.2

Noise-free estimation data

$\text{fit}(u, \hat{u}^{NARX})$ = 34.7 ± 9.3
$\text{fit}(u, \hat{u}^{NOE})$ = 27.2 ± 11.3
$\text{fit}(y, \hat{y}^{NARX})$ = 50.2 ± 9.1
$\text{fit}(y, \hat{y}^{NOE})$ = 25.4 ± 14.5

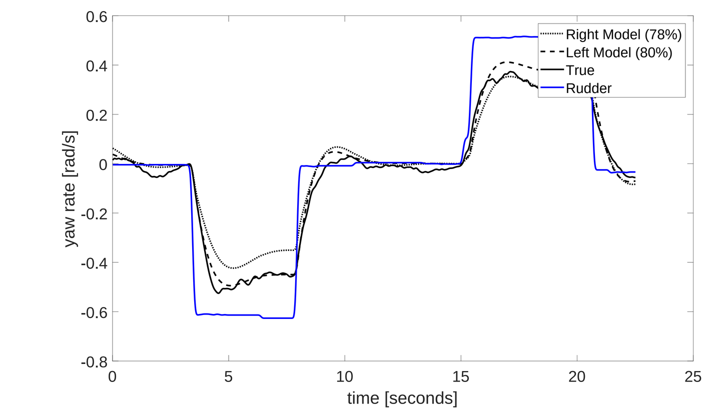
Real Data

Data from a laboratory site at the Norwegian University of Science and Technology (NTNU) was collected. A question was if this data could be used for revealing nonlinear rudder effects. The data was collected using a binary switching rudder angle, luckily with two different amplitude levels.

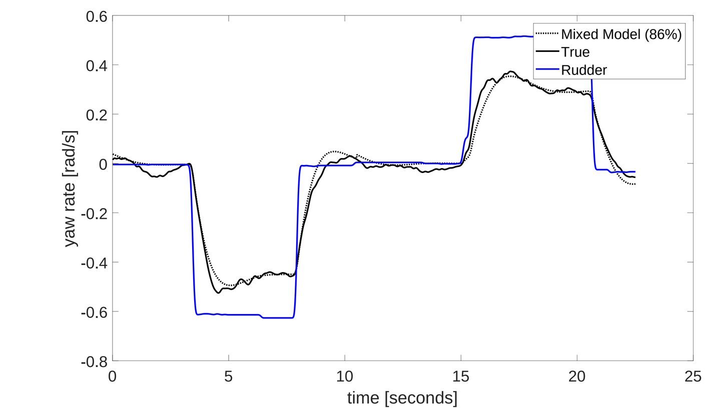
Estimated Models

Rudder angle to yaw rate

Linear models (ARX)

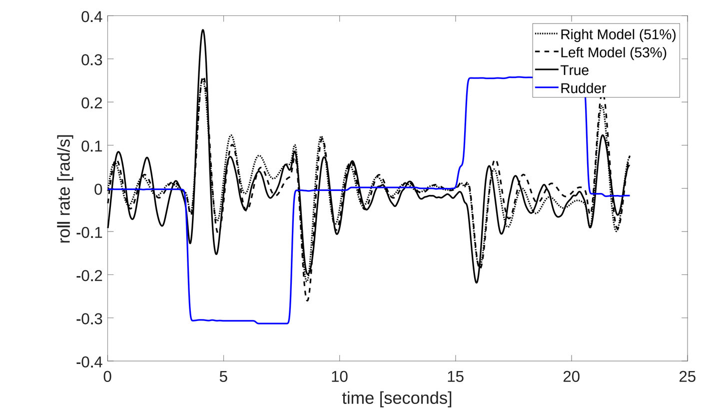


Piecewise linear model (ARX)

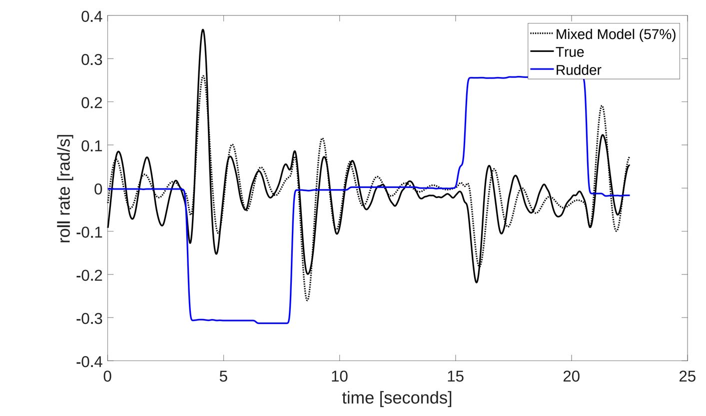


Rudder angle to roll rate

Linear models (OE)



Piecewise linear model (OE)



Observations

- There are benefits from acknowledging that the closed-loop relations are nonlinear.
- NOE models are more prone to overfitting than NARX models in the simulation examples.
- The rudder-to-yaw-rate dynamics could be captured, both with an autoregressive model and with an output-error model.
- The rudder-to-roll-rate dynamics could not be explained by an autoregressive model but could be described with an output-error model.
- There seem to be significant nonlinear effects in both cases.

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