

Hand in Assignment 2

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Estimators and least squares

1 Question 1: Unbiased estimate

- The unbiased estimator of θ , $\hat{\theta}$ is given as follows:

$$\hat{\theta} = E \left[\frac{1}{N-1} \sum_{i=1}^{N-1} \bar{x}_i \right] \quad (1)$$

where \bar{x}_i is the average of the sample x_i . The sample mean \bar{x}_i is given as:

$$\bar{x}_i = \frac{\theta}{2} \quad (2)$$

- Therefore the equation (1) can be written as:

$$\hat{\theta} = \frac{1}{N-1} E \left[\sum_{i=1}^{N-1} \left(\frac{\theta}{2} \right) \right] \quad (3)$$

$$= \frac{1}{N-1} \left[N-1 * \frac{\theta}{2} \right] \quad (4)$$

$$\hat{\theta} = \frac{\theta}{2} \quad (5)$$

which is the same as the population mean. Therefore $\hat{\theta}$ is the unbiased estimator for θ .

2 Question2: Linear least squares

2.1 2a: Least-squares estimate

- The linear system is given as:

$$y[k] = \theta u[k] + e[k] \quad (6)$$

the prediction is given as

$$\hat{y}[k] = \theta u[k] \quad (7)$$

with $e[k]$ belonging to $N(1, \sigma^2)$. The least-square estimate for θ is given as:

$$\hat{\theta}_{N-1} = \operatorname{argmin} V_{N-1}(\theta) \quad (8)$$

where $V_{N-1}(\theta)$ is calculated as follows:

$$V_{N-1}(\theta) = \frac{1}{N} \sum_{k=0}^{N-1} (y(k) - \hat{y}(k(\theta)))^2 \quad (9)$$

$$= \frac{1}{N} \sum_{k=0}^{N-1} (y(k) - \theta u[k])^2 \quad (10)$$

$$= \frac{1}{N} \left[\sum_{k=0}^{N-1} y^2[k] \right] + \theta \frac{1}{N} \left[\sum_{k=0}^{N-1} u[k]u[k]^T \right] \theta^T - 2\theta \frac{1}{N} \left[\sum_{k=0}^{N-1} y[k]u[k] \right] \quad (11)$$

$$= \frac{1}{N} \left[\sum_{k=0}^{N-1} y^2[k] \right] + \theta R_n \theta^T - 2\theta f_n \quad (12)$$

where $R_n = \frac{1}{N} \left[\sum_{k=0}^{N-1} u[k]u[k]^T \right]$ and $f_n = \frac{1}{N} \left[\sum_{k=0}^{N-1} y[k]u[k] \right]$

- Then equation(8) is minimum when

$$\hat{\theta}_{N-1} = R_n^{-1} f_n \quad (13)$$

$$\hat{\theta}_{N-1} = \frac{1}{N} \left[\sum_{k=0}^{N-1} u[k]u[k]^T \right]^{-1} \frac{1}{N} \left[\sum_{k=0}^{N-1} y[k]u[k] \right] \quad (14)$$

2.2 2b: Bias

- From equation (14) we have:

$$\hat{\theta}_{N-1} = \frac{1}{N} \left[\sum_{k=0}^{N-1} u[k]u[k]^T \right]^{-1} \frac{1}{N} \left[\sum_{k=0}^{N-1} y[k]u[k] \right] \quad (15)$$

$$= \frac{1}{N} \left[\sum_{k=0}^{N-1} u[k]u[k]^T \right]^{-1} \frac{1}{N} \left[\sum_{k=0}^{N-1} u[k] (u[k] + e[k]) \right] \quad (16)$$

the estimate for the above equation is calculated as follows

$$\mathbb{E} [\hat{\theta}_{N-1}] = \mathbb{E} \left[\frac{1}{N} \left[\sum_{k=0}^{N-1} u[k]u[k]^T \right]^{-1} \frac{1}{N} \left[\sum_{k=0}^{N-1} u[k] (\theta u[k] + e[k]) \right] \right] \quad (17)$$

$$= \frac{1}{N} \left[\sum_{k=0}^{N-1} u[k]u[k]^T \right]^{-1} \frac{1}{N} \mathbb{E} \left[\sum_{k=0}^{N-1} u[k] (\theta u[k] + e[k]) \right] \quad (18)$$

$$= \frac{1}{N} \left[\sum_{k=0}^{N-1} u[k]u[k]^T \right]^{-1} \frac{1}{N} \mathbb{E} \left[\sum_{k=0}^{N-1} \theta u[k]u[k]^T + u[k]e[k] \right] \quad (19)$$

simplifying the above equation we get the estimate in the form:

$$\mathbb{E} [\hat{\theta}_{N-1}] = \theta + \frac{1}{N} \left[\sum_{k=0}^{N-1} u[k]u[k]^T \right]^{-1} \frac{1}{N} \mathbb{E} \left[\sum_{k=0}^{N-1} u[k]e[k] \right] \quad (20)$$

- since the noise $e[k]$ has mean of 1 the term, $\mathbb{E} \left[\sum_{k=0}^{N-1} u[k]e[k] \right] \neq 0$. Therefore, $\mathbb{E} [\hat{\theta}_{N-1}]$ is not equal to θ and the estimate is said to be biased. The bias equation is given as:

$$\frac{1}{N} \left[\sum_{k=0}^{N-1} u[k]u[k]^T \right]^{-1} \frac{1}{N} \left[\sum_{k=0}^{N-1} u[k] \right] \quad (21)$$

2.3 2c: If $u[k] = 0$

- If $u[k] = 0$, then the estimate $\hat{\theta}$ doesn't exist and the output signal $y[k]$ does not contain any input variable other than the noise $e[k]$.

3 Question3: Curve fitting

3.1 3a

- The parameters that best fit the data are $\hat{\theta} = \begin{bmatrix} \hat{a} = -3.1160 \\ \hat{b} = 7.1840 \end{bmatrix}$.

Refer figure1 for the best fit plot.

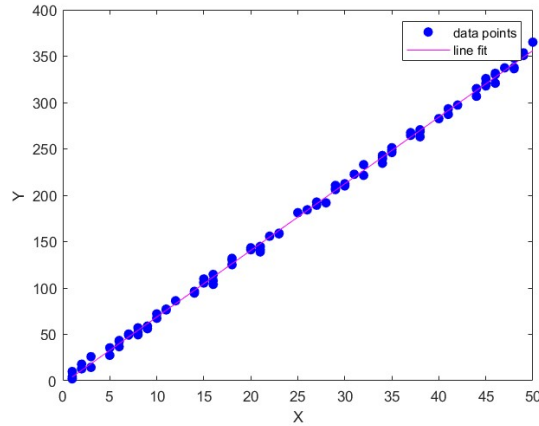


Figure 1

3.2 3b

- The parameters of the polynomial that best fit the data are $\hat{\theta} = \begin{bmatrix} \hat{a} = -2.5289 \\ \hat{b} = 6.4412 \\ \hat{c} = 2.8151 \end{bmatrix}$
- The parameters of the line that fit the data are $\hat{\theta} = \begin{bmatrix} \hat{a} = -1.1359e + 03 \\ \hat{b} = 146.7885 \end{bmatrix}$
- The prediction error of polynomial fit was: **8.3508** and the prediction error of line fit was: **282758.6138**. The polynomial Refer figure2 for the best fit plots.

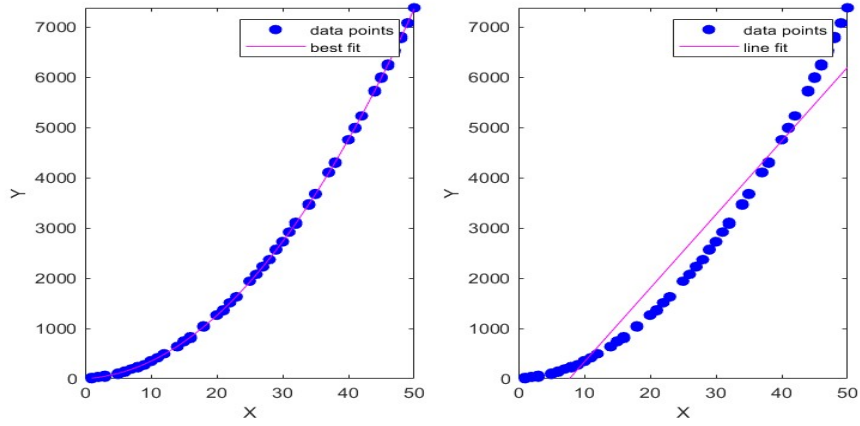


Figure 2

Identification of linear models for dynamical systems

4 Question1:One-step ahead predictor

4.1 1(a)

- The model structure is **ARMAX**.

4.2 1(b): Plant model and Noise model

For the model structure $y(t) + a_1y(t-1) + a_2y(t-2) = b_0u(t) + e(t) + c_1e(t-1)$

- The expressions of the plant model G and noise model H are as follows:

$$G(t|t-1, \theta) = \frac{b_0}{1 + a_1 \left(\frac{y(t-1)}{y(t)} \right) + a_2 \left(\frac{y(t-2)}{y(t)} \right)}; H(t|t-1, \theta) = \frac{1 + c_1 \left(\frac{e(t-1)}{e(t)} \right)}{1 + a_1 \left(\frac{y(t-1)}{y(t)} \right) + a_2 \left(\frac{y(t-2)}{y(t)} \right)} \quad (22)$$

4.3 1(c): One step ahead predictor

- The one step ahead predictor for given ARMAX model is as follows:

$$\hat{y}(t|t-1, \theta) = H^{-1}(q) G(q) u(t) + (1 - H^{-1}(q)) y(t) \quad (23)$$

$$\hat{y}(t|t-1, \theta) = \left(\frac{1 + c_1 q^{-1}}{a_1 q^{-1} + a_2 q^{-2}} \right)^{-1} \left(\frac{b_0}{a_1 q^{-1} + a_2 q^{-2}} \right) u(t) + \left[1 - \left(\frac{1 + c_1 q^{-1}}{a_1 q^{-1} + a_2 q^{-2}} \right)^{-1} \right] y(t) \quad (24)$$

simplifying the equation we get

$$\hat{y}(t|t-1, \theta) = \left[\frac{b_0}{1 + c_1 q^{-1}} \right] u(t) + \left[\frac{1 + c_1 q^{-1} - a_1 q^{-1} - a_2 q^{-2}}{1 + c_1 q^{-1}} \right] y(t) \quad (25)$$

4.4 1(d) Linearity of the predictor

- The equation (25) can be reduced to:

$$\hat{y}(t|t-1, \theta) = b_0 u(t) + (y(t-1) - \hat{y}(t|t-2, \theta)) c_1 + y(t) (1 - a_1 q^{-1} - a_2 q^{-1}) \quad (26)$$

it is in the form of

$$\hat{y}(t|t-1, \theta) = \theta^T \varphi(t, \theta) \quad (27)$$

From (26) and (27) the prediction $\hat{y}(t|t-1, \theta)$ is nonlinear in θ , since the vector $\varphi(t, \theta)$ now depends on θ .

5 Question2: Prediction or simulation?

5.1 2(a): Model structure

- The model structure is **OE**.

5.2 2(b): One step ahead predictor

- The 1-step ahead predictor is as follows:

$$y(t) = \frac{b_0}{1 + a_1 \left(\frac{y(t-1)}{y(t)} \right)} u(t) + e(t) \quad (28)$$

$$\hat{y}(t|t-1, \theta) = \frac{b_0}{1 + a_1 \left(\frac{y(t-1)}{y(t)} \right)} u(t) \quad (29)$$

rearranging (29) we get;

$$\hat{y}(t|t-1, \theta) = \left(1 - \frac{y(t-1)}{y(t)}\right) \hat{y}(t|t-1, \theta) + b_0 u(t) \quad (30)$$

from (30) since for an OE model, the predictor \hat{y} does not contain the previous values of the prediction error ($y(t) - \hat{y}(t|t-1, \theta)$), but rather contains the input signal $u(t)$ and the previous values $\hat{y}(t|t-1, \theta)$, the prediction may not yield good results if the output $y(t)$ has high transient behavior.

6 Question3: Identification of an ARX model

6.1 3(a): One step ahead predictor

- The parameters of each candidate ARX model, using the estimation data are as follows.

$$\text{for 12(a)} : \quad \hat{\theta} = \begin{bmatrix} \hat{b}_0 = 0.0688 \\ \hat{a}_1 = -0.9590 \\ \hat{a}_2 = 0.3567 \end{bmatrix} \quad (31)$$

$$\text{for 12(b)} : \quad \hat{\theta} = \begin{bmatrix} \hat{b}_0 = 0.0113 \\ \hat{b}_1 = 0.9946 \\ \hat{a}_1 = -0.8923 \\ \hat{a}_2 = 0.3116 \end{bmatrix} \quad (32)$$

$$\text{for 12(c)} : \quad \hat{\theta} = \begin{bmatrix} \hat{b}_1 = 1 \\ \hat{a}_1 = -1 \\ \hat{a}_2 = 0.6 \\ \hat{a}_3 = -0.3 \end{bmatrix} \quad (33)$$

$$(34)$$

6.2 3(b): Root Mean Square Error

- The **prediction errors** for the ARX models are as follows:

$$\text{for 12(a)} : 1.0582 \quad (35)$$

$$\text{for 12(b)} : 0.31664 \quad (36)$$

$$\text{for 12(c)} : 1.2215e^{-15} \quad (37)$$

- The **simulation errors** for the ARX models are as follows:

$$\text{for } 12(a) : 1.3941 \quad (38)$$

$$\text{for } 12(b) : 0.41933 \quad (39)$$

$$\text{for } 12(c) : 1.9358e^{-15} \quad (40)$$

- For both prediction and simulation the equation **12c** is the best model for the given data, since the error $(y(t) - \hat{y}(t|t-1, \theta))$ and its RMS value are the least for **12c**.