

# Nonlinear ARX identification

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# Description of the problem

# What is an ARX model?

- Autoregressive with exogenous input model:

previous **outputs** & knowledge about the **input** → current **output**

- Black-box model
- Dynamical system (initial conditions)
- For the inputs  $u$  and outputs  $y$ , with an order of the dynamics of  $n_a$  and  $n_b$  and the parameters  $a_{n_a}$  and  $b_{n_b}$ , the general form of the ARX can be written as:

$$y(k) = -y(k-1) - y(k-2) \dots - y(k-n_a) + u(k-1) + u(k-2) \dots + u(k-n_b) + e(k)$$

# Delay vector

- Therefore, the **delayed** outputs and inputs vector can be computed:

$$d(k) = [y(k-1), y(k-2), \dots, y(k-n_a), u(k-n_k), u(k-n_k-1), \dots, u(k-n_k-n_b+1)]^T$$

- By applying the polynomial function to  $d(k)$ , we get our solution:

$$\hat{y}(k) = f(y(k-1), y(k-2), \dots, y(k-n_a), u(k-1), u(k-2), \dots, u(k-n_b))$$

# Polynomial approximator

- For example, having an **order of dynamics** of  $n_a = n_b = n_k = 1$ , and an **order of the polynomial** of  $m = 2$ , we will have 2 inputs for our function. Using the notation  $y(k - 1) = x_1$  and  $u(k - 1) = x_2$ , the polynomial becomes:

$$\hat{y}(k) = [1 \ x_1 \ x_2 \ x_1^2 \ x_2^2 \ x_1 x_2] \cdot \theta$$

where  $\theta = [a_1 \ \dots \ a_{n_a} \ b_1 \ \dots \ b_{n_b}]^T$

Approximator function

# Functions

- *delay* function – computes the past input and outputs using the given mathematical formula and creates a matrix for each step k
- *powers* function – generates the powers for every input of our polynomial;
  - returns a matrix of N x no. of inputs, where N – number of all possible combinations with repetitions

For 2 inputs and m=2, we get:

$$\begin{bmatrix} 2 & 0 \\ 1 & 1 \\ 0 & 2 \end{bmatrix}$$



# Functions

- *reg* function – the **columns** of the delay vector are raised at each **row** of the power matrix (element-wise):

$$[x_1 \ x_2] \cdot ^{[2 \ 0]} = [x_1^2 \ x_2^0]$$

$$[x_1 \ x_2] \cdot ^{[1 \ 1]} = [x_1^1 \ x_2^1]$$

$$[x_1 \ x_2] \cdot ^{[0 \ 2]} = [x_1^0 \ x_2^2]$$

- Therefore,  $\varphi_{power=2} = [x_1^2 x_2^0 \ x_1^1 x_2^1 \ x_1^0 x_2^2]$  for each step k.
- *regressor* function – creates the regressor matrix (calls reg function for power 1 to m)

# Parameters

- Nonlinear model & linear parameters
- Linear regression can still be used, so, following the further equation:

$$Y = \phi \cdot \theta$$

- $Y$  – the output (in this case, taken from the training dataset)
- $\phi$  – the regressor (computed using the training dataset)
- $\theta$  – the parameter vector (unknown)
- we can perform left multiplication with  $(\phi^T \phi)^{-1} \phi^T$ , hence:

$$\theta = (\phi^T \phi)^{-1} \phi^T Y$$

# Key features

# Approximator function

- Multiply inputs at each iteration:

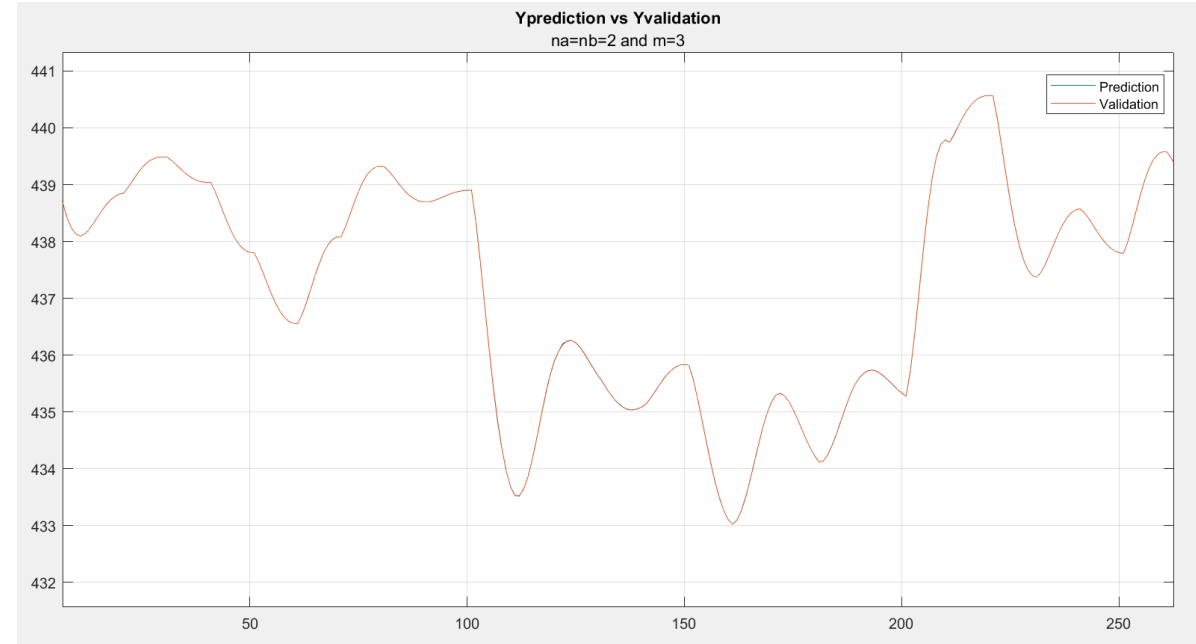
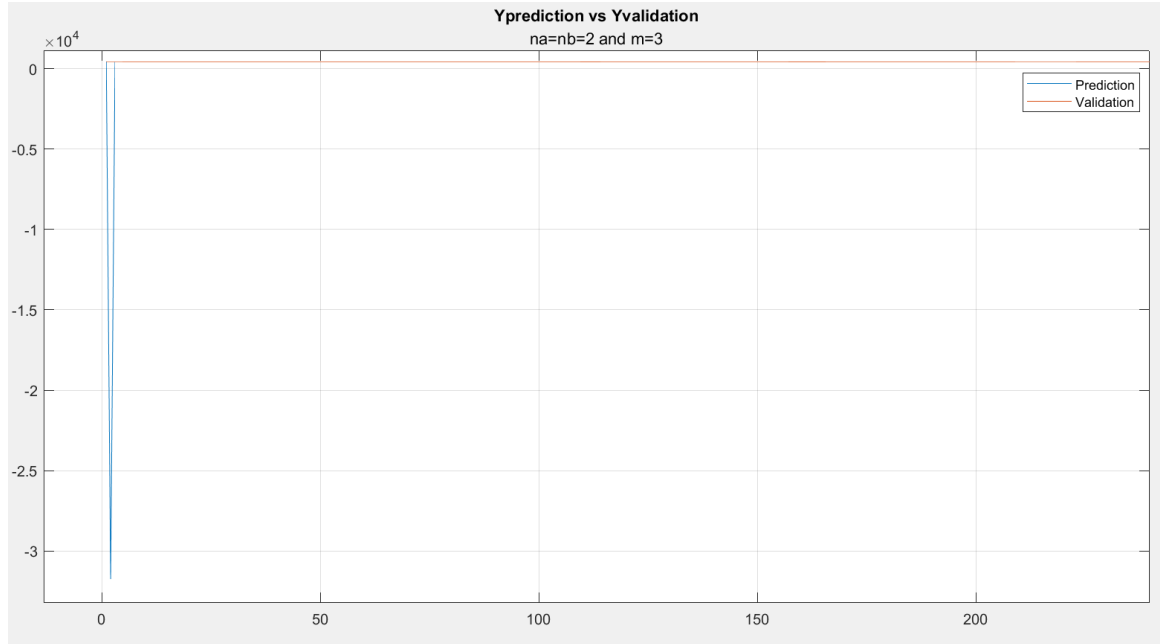
$$x_1x_2x_3 \quad x_1x_2x_3 \quad \dots \quad x_1x_2x_3$$

- *nchoosek* (Matlab function) – combinations of elements from a given vector, sizing them as specified
- Assuring repetition – copying the vector a number of times (*number of columns* times)
  - If the number of columns is 3 and m=2, then:

$$v = [0 \ 1 \ 2] \rightarrow v = [0 \ 1 \ 2 \ 0 \ 1 \ 2 \ 0 \ 1 \ 2]$$

- Imposing 2 conditions: unique rows and sum of the elements equal to m

# Corrections

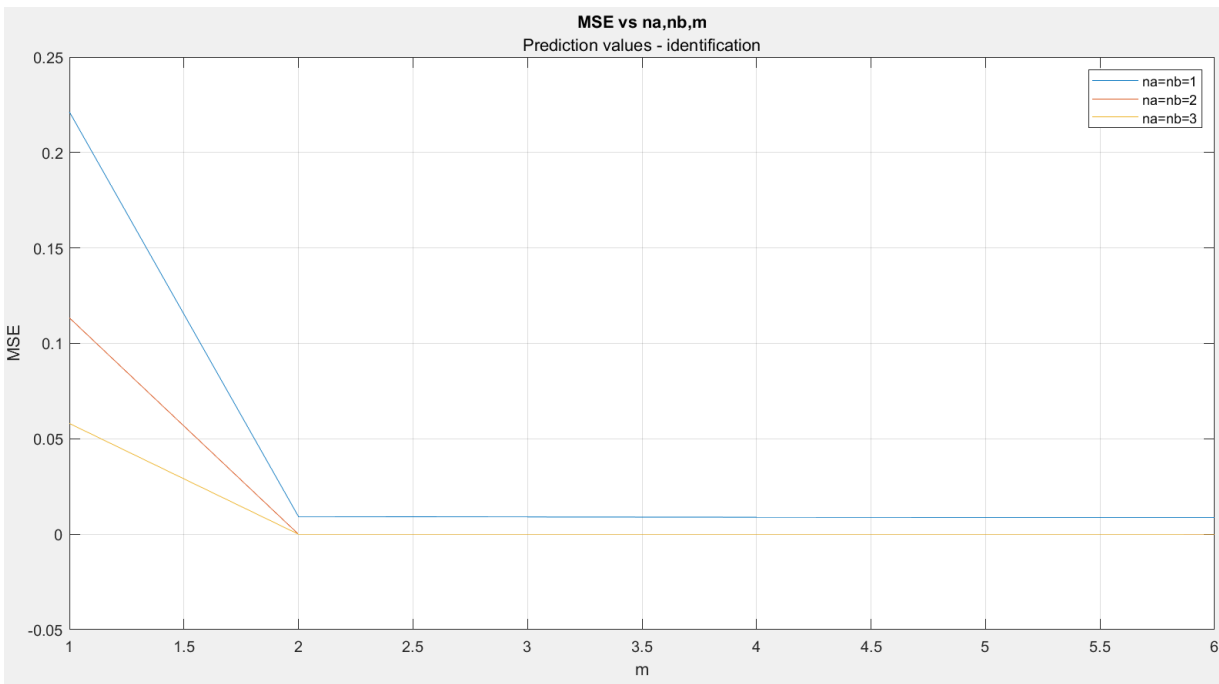


- Observations:
  - few out of range value could be neglected
  - very similar values with the true ones
  - ensuring corrections

# Tuning results

# Identification dataset

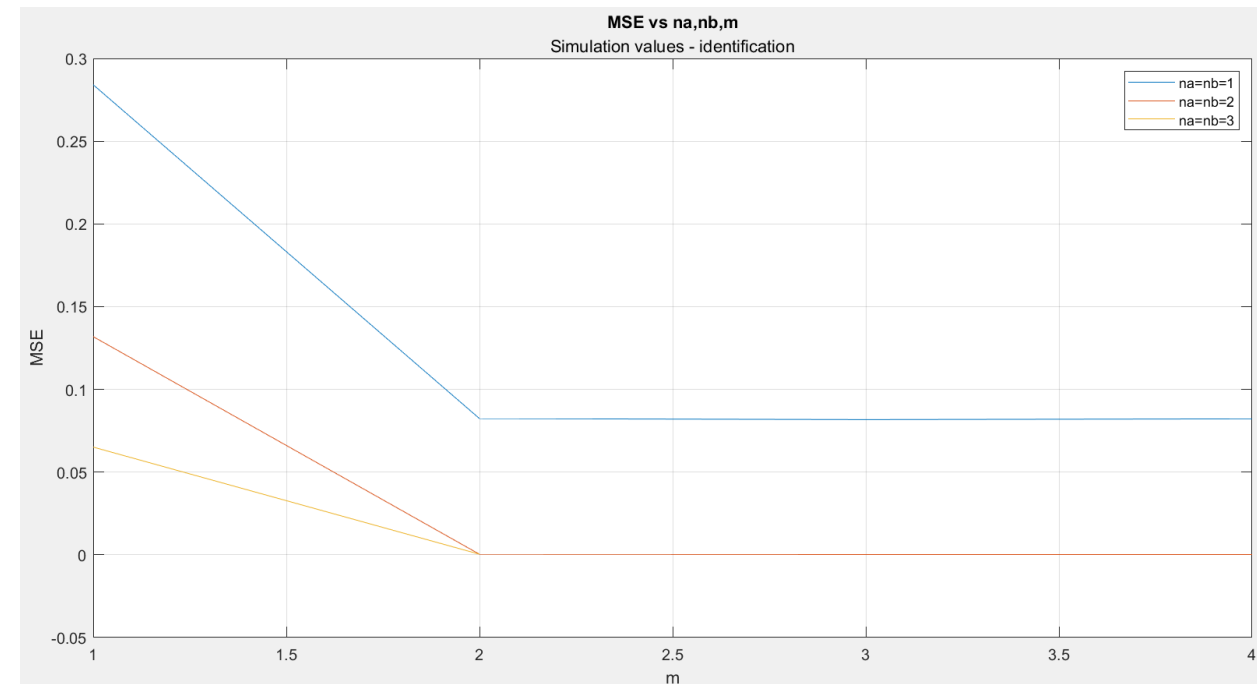
## Prediction



Best values for:

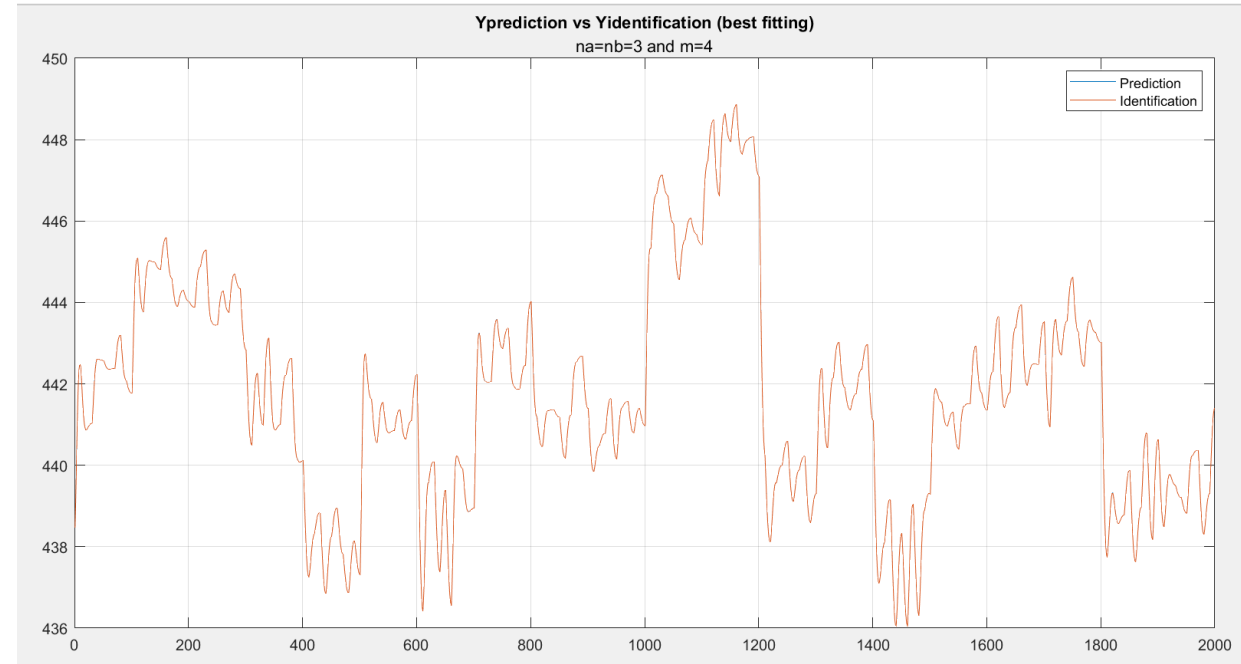
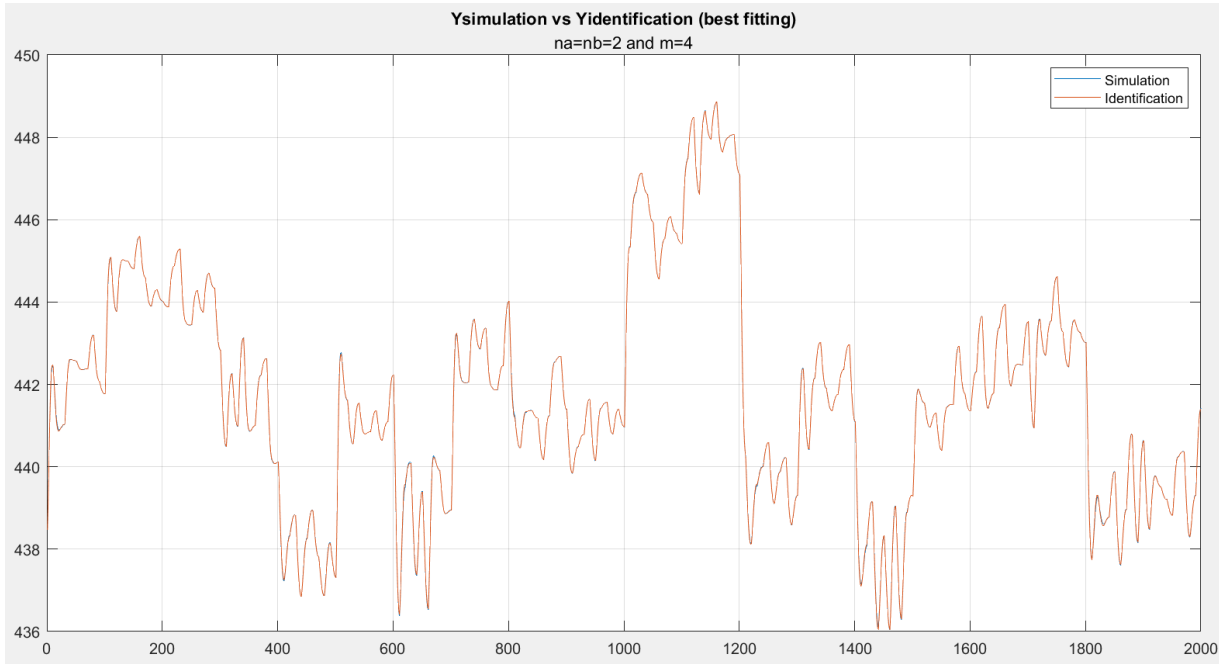
$$\text{MSE} = 1.53 \cdot 10^{-6} \quad (n_a = n_b = 3 \text{ and } m = 4)$$

## Simulation



$$\text{MSE} = 1.65 \cdot 10^{-4} \quad (n_a = n_b = 2 \text{ and } m = 4)$$

# Identification dataset

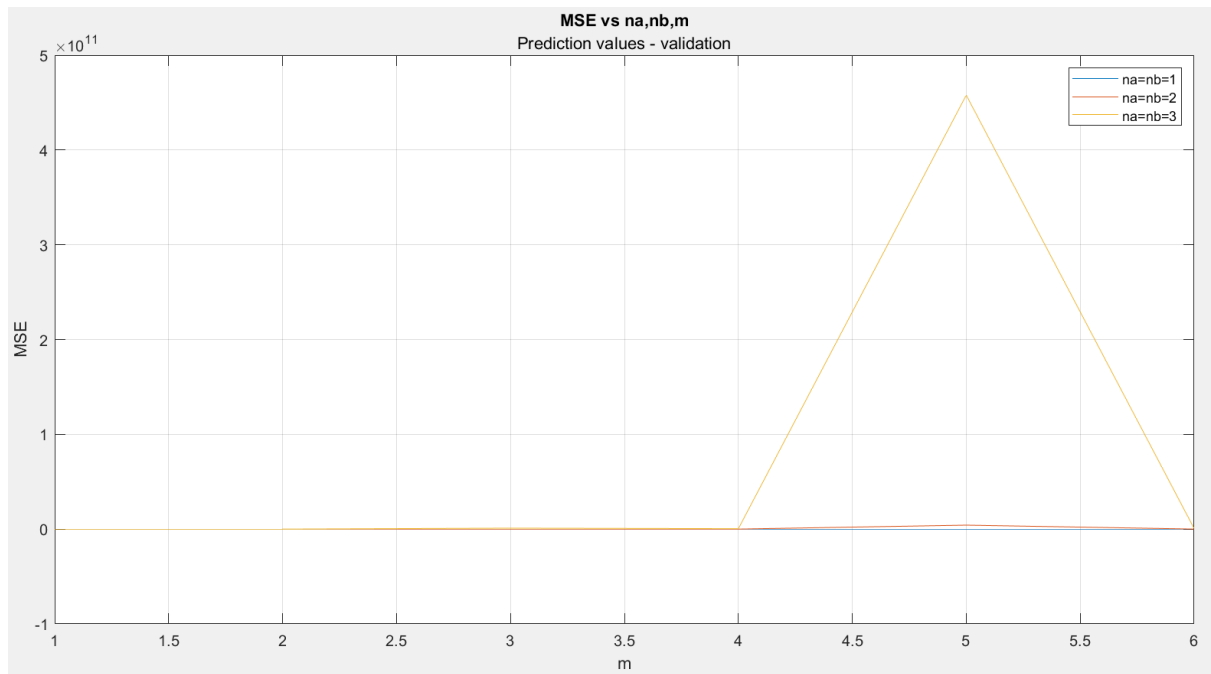


- Observations:
  - overfitting
  - similarity
  - approximately large order



# Validation dataset

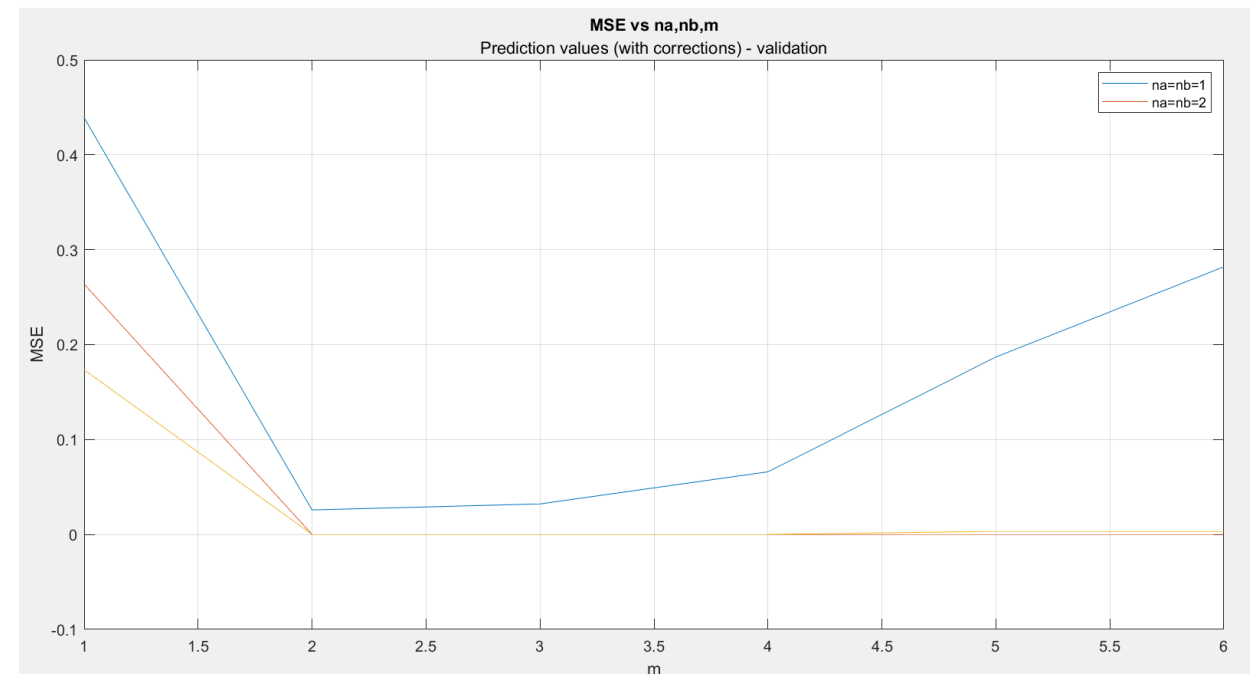
## Prediction without corrections



Best values for:

$$\text{MSE} = 0.0316 \ (n_a = n_b = 1 \text{ and } m = 2)$$

## Prediction with corrections



$$\text{MSE} = 2.06 \cdot 10^{-5} \ (n_a = n_b = 3 \text{ and } m = 2)$$

# Validation dataset

## Simulation

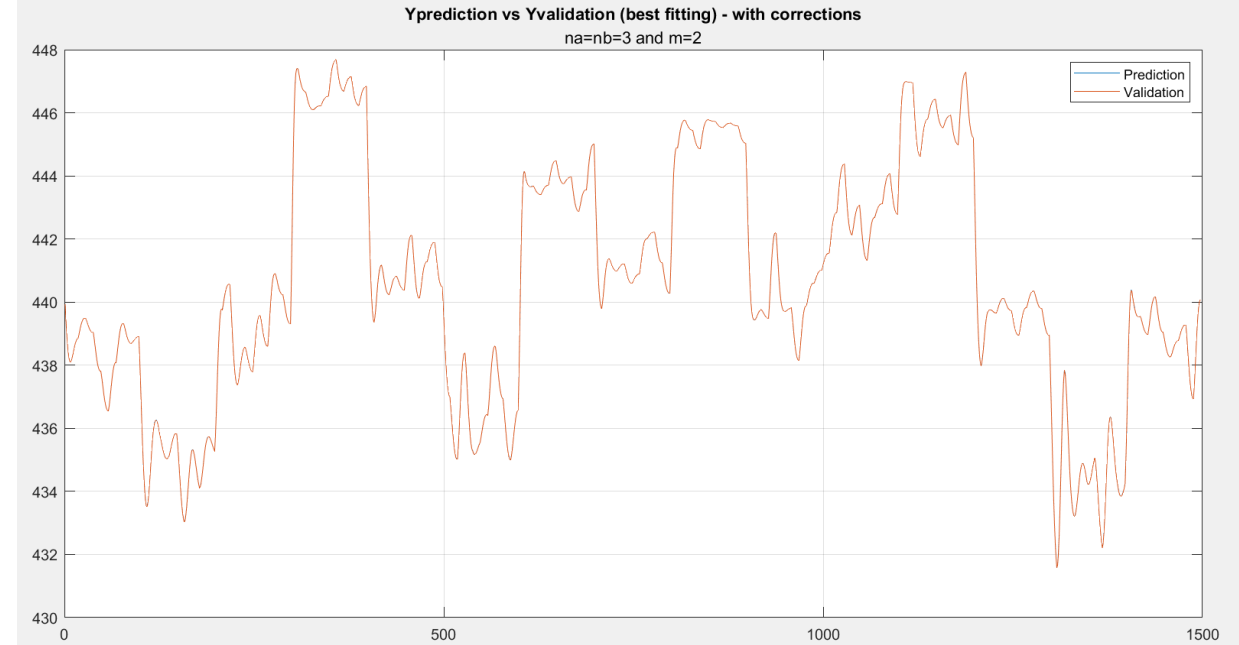
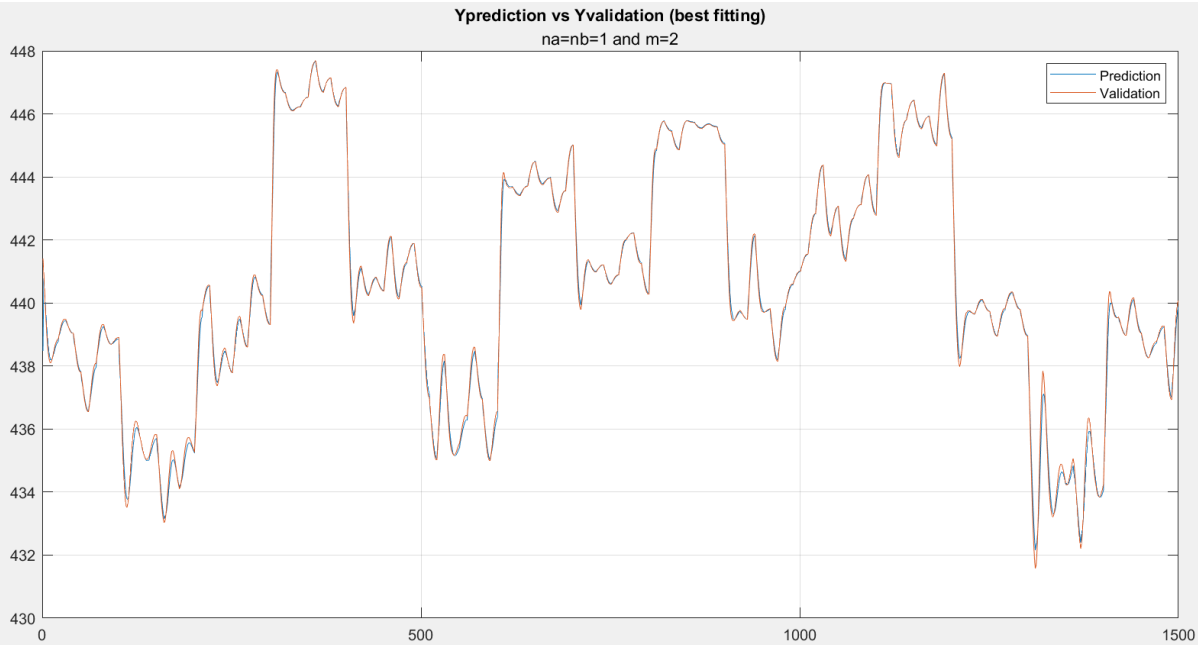
	$m = 1$	$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$
$n_a = n_b = 1$	0.57177	0.26917	0.82594	<i>NaN</i>	<i>NaN</i>	<i>NaN</i>
$n_a = n_b = 2$	0.32082	<i>NaN</i>	<i>NaN</i>	<i>NaN</i>	<i>NaN</i>	<i>NaN</i>
$n_a = n_b = 3$	0.21043	<i>NaN</i>	<i>NaN</i>	<i>NaN</i>	<i>NaN</i>	<i>NaN</i>

- Observations:
  - unstable model
  - very small values of the parameters

Best values for:

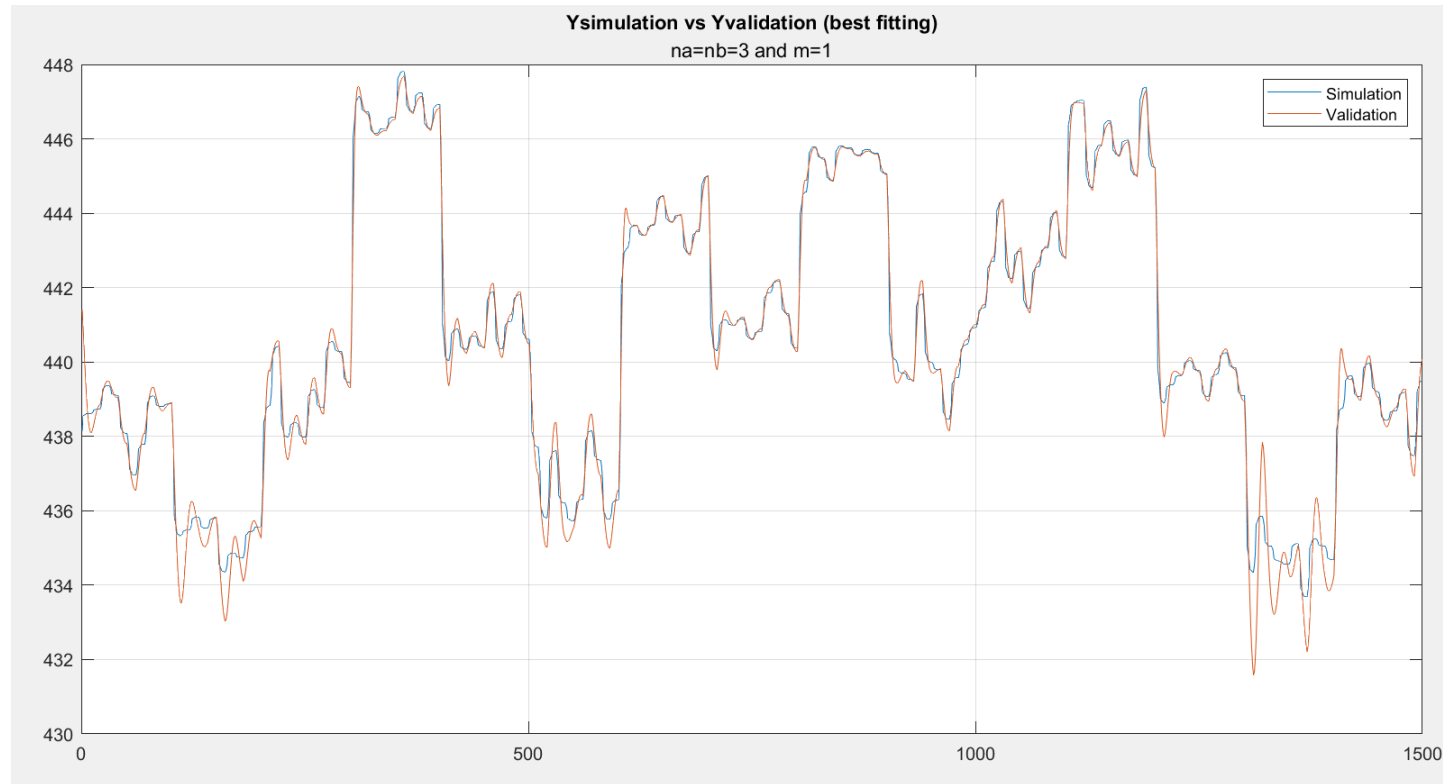
$$\text{MSE} = 0.21043 \text{ } (n_a = n_b = 3 \text{ and } m = 1)$$

# Validation dataset



- Observations:
  - corrections – if the value is not in the range => exclude (plot 2)
  - overfitting (plot 2)
  - small order system (for both orders) (plot 1)

# Validation dataset



- Observations:
  - noticeable difference between prediction and simulation
  - large order of dynamics, small order of the polynomial

# Conclusion

# Prediction vs. Simulation

- Prediction (more knowledge about the model)
  - open-loop system
  - “memory” of the ARX model
  - uses **true past output values** in order to predict the output at time  $k$
  - precise values (maybe even cases of overfitting)
  - more accuracy  $\Rightarrow$  more certainty about the real-time output
- Simulation (less knowledge about the model)
  - closed-loop system
  - uses **previously computed values** in order to predict the output at time  $k$  (dynamical model)
  - approximately good results for small orders
  - very poor results for large orders (leading to instability)
  - can be used even if we know just the inputs of our model

# Nonlinear ARX model

- Generalization of the ARX model
- Applied to various dynamical systems
- The prediction itself can be used in a wide range of domains