

By Rus Alexandru, Pal Robert and Suciu Andrei

Problem Statement

Develop a *nonlinear ARX* model to approximate the dynamics of an *unknown system* with one input and noisy outputs using polynomial regression.

Objectives:

- Configure Polynomial ARX Model
- Identify Model Parameters
- Evaluate Predictive and Simulative Accuracy
- Analyze Model Performance

Approximator Structure

- Polynomial order *m* is incrementally tested to optimize model accuracy.
- Built from delayed inputs and outputs, creating a regression matrix.

$$arPhi = [1, y(k-1), \dots, y(k-na), u(k-nk), \dots, u(k-nk-nb+1), y(k-1)^2, \dots]$$

 \bullet Parameters θ are estimated using linear regression.

$$heta = (oldsymbol{\phi}^ opoldsymbol{\phi})^{-1}oldsymbol{\phi}^ op y \qquad \hat{y} = oldsymbol{\phi} heta$$

Approximator Structure

MSE Evaluation:

$$MSE = rac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$

- Optimal Model Selection:
 - Explore combinations of na,nb,m.
 - Select the configuration with the lowest validation MSE.
 - Save the identified parameters for final predictions.

Key features:

• The *monomial term generator* efficiently creates polynomial expansions for delayed inputs (u) and outputs (y).

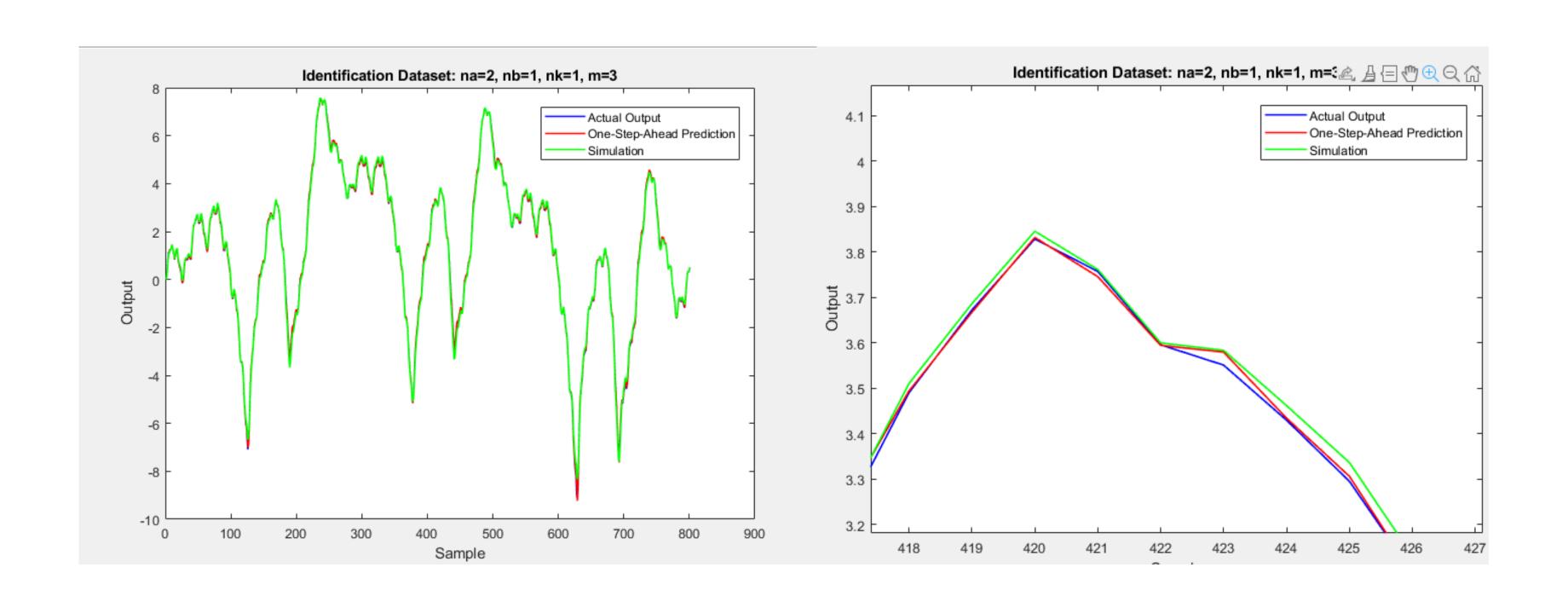
Visualization of Polynomial Terms for Degree m = 2

$$Constant\ Term: arPhi_1 = 1 \ First-Degree\ Terms: arPhi_2 = y(k-1), y(k-2), u(k-1) \ Second-Degree\ Terms: arPhi_3 = y(k-1)^2, y(k-2)^2, u(k-1)^2, y(k-1)y(k-2), \ y(k-1)u(k-1), y(k-2)u(k-1)$$

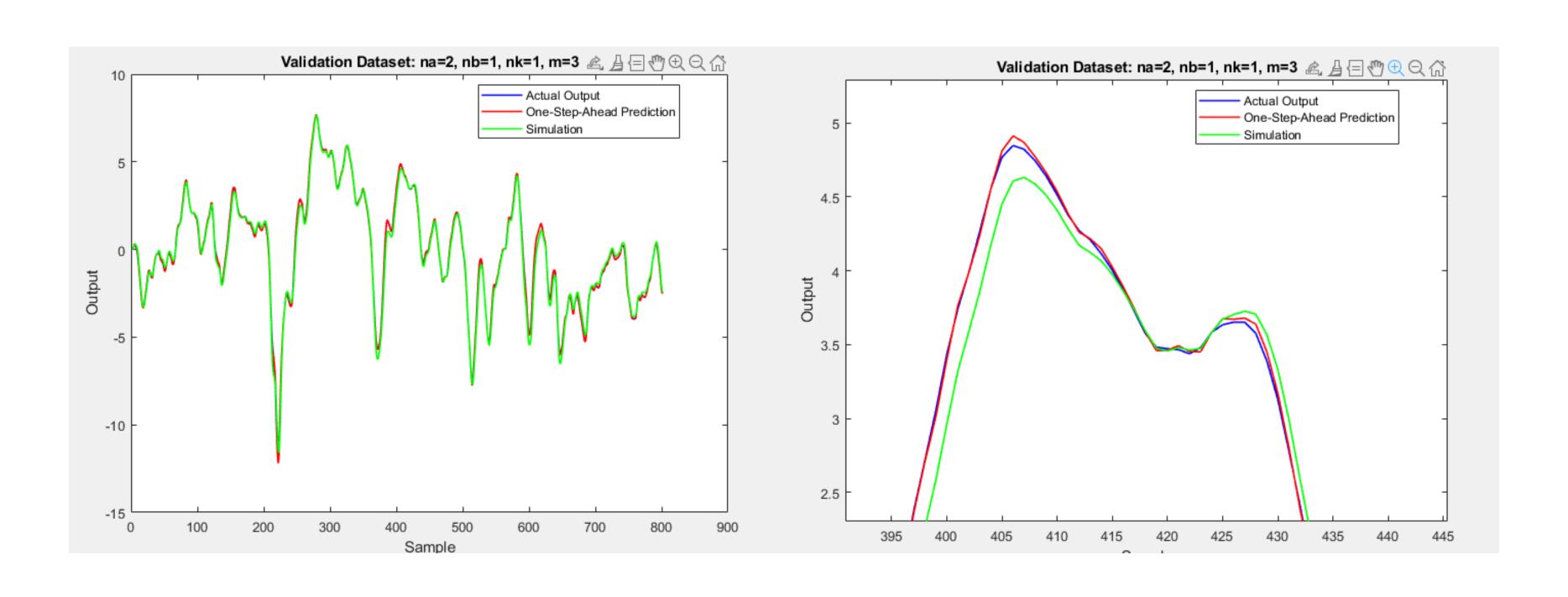
Tuning Results - MSE

	na	nb	m	MSE y_{pred} (ID)	MSE y_{sim} (ID)	MSE y_{pred} (VAL)	MSE y_{sim} (VAL)
1	1.0000	1.0000	1.0000	0.0076	0.1633	0.0172	0.2763
2	1.0000	1.0000	2.0000	0.0033	0.0396	0.0104	0.1823
3	1.0000	1.0000	3.0000	0.0027	0.0290	0.0100	0.1847
4	1.0000	2.0000	1.0000	0.0076	0.1626	0.0171	0.2770
5	1.0000	2.0000	2.0000	0.0033	0.0404	0.0105	0.1901
6	1.0000	2.0000	3.0000	0.0025	0.0287	0.0104	0.1949
7	1.0000	3.0000	1.0000	0.0078	0.1632	0.0171	0.2775
8	1.0000	3.0000	2.0000	0.0034	0.0416	0.0105	0.1953
9	1.0000	3.0000	3.0000	0.0027	0.0297	0.0105	0.2018
10	1.0000	4.0000	1.0000	0.0087	0.1688	0.0171	0.2775
11	1.0000	4.0000	2.0000	0.0043	0.0466	0.0104	0.2001
12	1.0000	4.0000	3.0000	0.0035	0.0344	0.0106	0.2062
13	2.0000	1.0000	1.0000	0.0065	0.1826	0.0133	0.2799
14	2.0000	1.0000	2.0000	0.0019	0.0179	0.0052	0.0833
15	2.0000	1.0000	3.0000	0.0014	0.0147	0.0050	0.0825
16	2.0000	2.0000	1.0000	0.0031	0.1775	0.0041	0.2783
17	2.0000	2.0000	2.0000	0.0017	NaN	9.7510	NaN
18	2.0000	2.0000	3.0000	0.0013	NaN	25.3965	NaN
19	2.0000	3.0000	1.0000	0.0032	0.1900	0.0041	0.2779

Tuning Results - MSE Identification



Tuning Results - MSE Validation



Overall Conclusion

- The chosen nonlinear ARX model achieves low MSE, balancing accuracy and simplicity.
- The polynomial term generator ensures efficient and flexible model construction.
- Validation results confirm strong generalization and reliable performance on unseen data.

```
load('iddata-07.mat');
u = id.u;
y = id.y;
Ts = id.Ts;
u_val = val.u;
y_val = val.y;
N_val = length(y_val);
na max = 4;
nb_max = 4;
m_m = 3;
nk = 1;
N = length(y);
results = [];
for na = 1:na_max
    for nb = 1:nb_max
        for m = 1:m_max
            Phi = [];
            for k = max(na, nb + nk):N
                delayed_y = zeros(1, na);
                for j = 1:na
                    if (k - j) > 0
                        delayed_y(j) = y(k - j);
                    end
                end
                delayed_u = zeros(1, nb);
                for j = 1:nb
                    if (k - nk - j + 1) > 0
                        delayed_u(j) = u(k - nk - j + 1);
                    end
                end
                delayed_vars = [delayed_y, delayed_u];
                poly terms = [1, monomial terms(delayed vars, m)];
                Phi = [Phi; poly_terms];
            end
            y_regress = y(max(na, nb + nk):end);
            theta = Phi \ y regress;
            y_pred = zeros(N,1);
            for k = max(na, nb + nk):N
                delayed_y = zeros(1, na);
                for j = 1:na
                    if (k - j) > 0
                        delayed_y(j) = y(k - j);
                    end
                end
                delayed_u = zeros(1, nb);
                for j = 1:nb
                    if (k - nk - j + 1) > 0
                        delayed_u(j) = u(k - nk - j + 1);
                    end
                end
```

```
delayed_vars = [delayed_y, delayed_u];
    poly_terms = [1, monomial_terms(delayed_vars, m)];
    y_pred(k) = poly_terms * theta;
end
y_{sim} = zeros(N,1);
for k = max(na, nb + nk):N
    delayed_y = zeros(1, na);
    for j = 1:na
        if(k-j)>0
            delayed_y(j) = y_sim(k - j);
        end
    end
    delayed_u = zeros(1, nb);
    for j = 1:nb
        if (k - nk - j + 1) > 0
            delayed_u(j) = u(k - nk - j + 1);
        end
    end
    delayed vars = [delayed y, delayed u];
    poly_terms = [1, monomial_terms(delayed_vars, m)];
    y_sim(k) = poly_terms * theta;
end
mse_pred = mean((y - y_pred).^2);
mse\_sim = mean((y - y\_sim).^2);
y_pred_val = zeros(N_val,1);
for k = max(na, nb + nk):N_val
    delayed_y = zeros(1, na);
    for j = 1:na
        if(k-j)>0
            delayed_y(j) = y_val(k - j);
        end
    end
    delayed_u = zeros(1, nb);
    for j = 1:nb
        if (k - nk - j + 1) > 0
            delayed_u(j) = u_val(k - nk - j + 1);
        end
    end
    delayed_vars = [delayed_y, delayed_u];
    poly_terms = [1, monomial_terms(delayed_vars, m)];
    y_pred_val(k) = poly_terms * theta;
end
y sim val = zeros(N val,1);
for k = max(na, nb + nk):N_val
    delayed_y = zeros(1, na);
    for j = 1:na
        if(k - j) > 0
            delayed_y(j) = y_sim_val(k - j);
        end
    end
```

```
delayed_u = zeros(1, nb);
                for j = 1:nb
                    if (k - nk - j + 1) > 0
                        delayed_u(j) = u_val(k - nk - j + 1);
                    end
                end
                delayed vars = [delayed y, delayed u];
                poly_terms = [1, monomial_terms(delayed_vars, m)];
                y_sim_val(k) = poly_terms * theta;
            end
            mse_pred_val = mean((y_val - y_pred_val).^2);
            mse_sim_val = mean((y_val - y_sim_val).^2);
            results = [results; na, nb, m, mse_pred, mse_sim, mse_pred_val,
mse_sim_val];
        end
    end
end
fig = uifigure('Name', 'MSE Results', 'Position', [100, 100, 1000, 400]);
uitable(fig, 'Data', results, ...
    'ColumnName', {'na','nb','m','MSE y_{pred} (ID)','MSE y_{sim} (ID)','MSE
y_{pred} (VAL)','MSE y_{sim} (VAL)'}, ...
    'Position', [25, 50, 950, 300], 'FontSize', 12);
na = 2; nb = 1; m = 3;
Phi = [];
for k = max(na, nb + nk):N
    delayed_y = zeros(1, na);
    for j = 1:na
        if (k - j) > 0
            delayed_y(j) = y(k - j);
        end
    end
    delayed_u = zeros(1, nb);
    for j = 1:nb
        if (k - nk - j + 1) > 0
            delayed_u(j) = u(k - nk - j + 1);
        end
    end
    delayed_vars = [delayed_y, delayed_u];
    poly_terms = [1, monomial_terms(delayed_vars, m)];
    Phi = [Phi; poly terms];
end
y_regress = y(max(na, nb + nk):end);
theta = Phi \ y regress;
y_pred = zeros(N,1);
for k = max(na, nb + nk):N
    delayed_y = zeros(1, na);
    for j = 1:na
        if (k - j) > 0
            delayed_y(j) = y(k - j);
        end
```

```
end
    delayed_u = zeros(1, nb);
    for j = 1:nb
        if (k - nk - j + 1) > 0
            delayed_u(j) = u(k - nk - j + 1);
        end
    end
    delayed_vars = [delayed_y, delayed_u];
    poly_terms = [1, monomial_terms(delayed_vars, m)];
    y pred(k) = poly terms * theta;
end
y_{sim} = zeros(N,1);
for k = max(na, nb + nk):N
    delayed_y = zeros(1, na);
    for j = 1:na
        if (k - j) > 0
            delayed_y(j) = y_sim(k - j);
        end
    end
    delayed_u = zeros(1, nb);
    for j = 1:nb
        if (k - nk - j + 1) > 0
            delayed_u(j) = u(k - nk - j + 1);
        end
    end
    delayed_vars = [delayed_y, delayed_u];
    poly_terms = [1, monomial_terms(delayed_vars, m)];
    y_sim(k) = poly_terms * theta;
end
u_val = val.u;
y_val = val.y;
N_val = length(y_val);
y_pred_val = zeros(N_val,1);
for k = max(na, nb + nk):N_val
    delayed_y = zeros(1, na);
    for j = 1:na
        if (k - j) > 0
            delayed_y(j) = y_val(k - j);
        end
    end
    delayed_u = zeros(1, nb);
    for j = 1:nb
        if (k - nk - j + 1) > 0
            delayed_u(j) = u_val(k - nk - j + 1);
        end
    end
    delayed_vars = [delayed_y, delayed_u];
    poly_terms = [1, monomial_terms(delayed_vars, m)];
    y_pred_val(k) = poly_terms * theta;
end
```

```
y sim val = zeros(N val,1);
for k = max(na, nb + nk):N_val
    delayed y = zeros(1, na);
    for j = 1:na
        if (k - j) > 0
            delayed_y(j) = y_sim_val(k - j);
        end
    end
    delayed_u = zeros(1, nb);
    for j = 1:nb
        if (k - nk - j + 1) > 0
            delayed_u(j) = u_val(k - nk - j + 1);
        end
    end
    delayed_vars = [delayed_y, delayed_u];
    poly terms = [1, monomial terms(delayed vars, m)];
    y_sim_val(k) = poly_terms * theta;
end
figure('Name','Identification Results','NumberTitle','off');
plot(y,'b','LineWidth',1.2); hold on; plot(y_pred,'r','LineWidth',1.2);
plot(y_sim,'g','LineWidth',1.2);
legend('Actual Output','One-Step-Ahead Prediction','Simulation','Location','Best');
title(sprintf('Identification Dataset: na=%d, nb=%d, nk=%d, m=%d',na,nb,nk,m));
xlabel('Sample'); ylabel('Output');
figure('Name','Validation Results','NumberTitle','off');
plot(y_val, 'b', 'LineWidth',1.2); hold on; plot(y_pred_val, 'r', 'LineWidth',1.2);
plot(y_sim_val, 'g', 'LineWidth', 1.2);
legend('Actual Output','One-Step-Ahead Prediction','Simulation','Location','Best');
title(sprintf('Validation Dataset: na=%d, nb=%d, nk=%d, m=%d',na,nb,nk,m));
xlabel('Sample'); ylabel('Output');
function terms = monomial terms(vars, degree)
num_vars = length(vars);
terms = [];
for d = 1:degree
    for i = 1:num vars
        terms = [terms, vars(i)^d];
    end
end
end
```