RECEDING HORIZON
MODIFIED ITERAT
PROGRAMMING AND I
MODE

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N CONTROL USING ATIVE DYNAMIC D NEURAL NETWORK DELS

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Aims

- To speed up original Iterative Dynamic Programming,
- Modified IDP: use of discrete-time, input-output models,
- Use of the Receding horizon principle,
- Application to biochemical reactor identified by Artificial Neural Network model.

Description of controlled system

Controlled system: NARX

$$\hat{\boldsymbol{y}}_M(t) = \boldsymbol{g}(\boldsymbol{w}, \hat{\boldsymbol{y}}_M(t-1), \hat{\boldsymbol{y}}_M(t-2), \ldots, \boldsymbol{u}(t-1), \boldsymbol{u}(t-2), \ldots)$$

Disturbance:

$$\hat{\boldsymbol{y}}(t+i) = \hat{\boldsymbol{y}}_M(t+i) + \boldsymbol{d}(t)$$

Disturbance estimation: (constant in the future)

$$\boldsymbol{d}(t+i) = \boldsymbol{d}(t) = \boldsymbol{y}(t) - \hat{\boldsymbol{y}}_M(t)$$

Modified IDP - definition

Input constraints for piece-wise constrant control $\boldsymbol{u}$:

$$\boldsymbol{u}^{min} \leq \boldsymbol{u}(t+j) \leq \boldsymbol{u}^{max}$$

Cost function:

$$J = F(\hat{\boldsymbol{y}}(t+1), \ldots, \hat{\boldsymbol{y}}(t+P), \boldsymbol{u}(t), \boldsymbol{u}(t+1), \ldots, \boldsymbol{u}(t+P-1))$$

IDP parameters:

P - number of stages (or equivalently prediction horizon),

M - number of generated control actions,

N - number of $\boldsymbol{y}$-grid points,

r^1 - initial size of control region,

φ - contraction factor, $\varphi \in [0.7 - 0.9]$,

N_i - number of iterations,

n - number of steps for which the output trajectories are compared

Modified IDP - algorithm

1. Choose N control trajectories by perturbing the optimal (or initial if $i = 1$) control trajectory trajectory $\boldsymbol{u}^{i-1} = [\boldsymbol{u}^{i-1}(t), \ldots, \boldsymbol{u}^{i-1}(t+P-1)]$

2. Use the N control trajectories to obtain N system output trajectories for interval within the prediction horizon P

3. Start at the last stage P and generate for each $\hat{\boldsymbol{y}}(t+P-1)$-grid point M admissible values for control by:

$$\boldsymbol{u}^{i}(t+P-1) = \boldsymbol{u}^{i-1}(t+P-1)\boldsymbol{D}_{rand}r^{i}$$

   and find the one that is optimal by simulating the process model

4. Step back to stage $P-1$ and again generate M control actions given by previous equation and simulate the system on the stage $P-1$. In the interval P the best control policy is chosen as follows. Compare output trajectories n stages back and choose the best fit. The model is simulated with this control trajectory vector. Store the best control trajectory.

5. Repeat the previous step until the initial time is reached and choose the control trajectory that minimises performance index.

6. Reduce the admissible control region

$$r^{i+1} = \varphi r^{i}$$

and increase iteration index $i = i + 1$. The procedure is repeated for a specific number of iterations N_i.

Controlled system - Bioreactor

Process: CSTR, growth of *Saccharomyces cerevisiae* on glucose with continuous feeding

Input: gas dilution rate ($D_g(t)$

$$0 \leq D_g \leq 3 \; [\mathrm{l}^{-1}].$$

Output: dissolved oxygen concentration ($c_o(t)$)

Sampling time: 0.5 h

Process model: Artificial Neural network

Simulation Parameters

Network parameters:

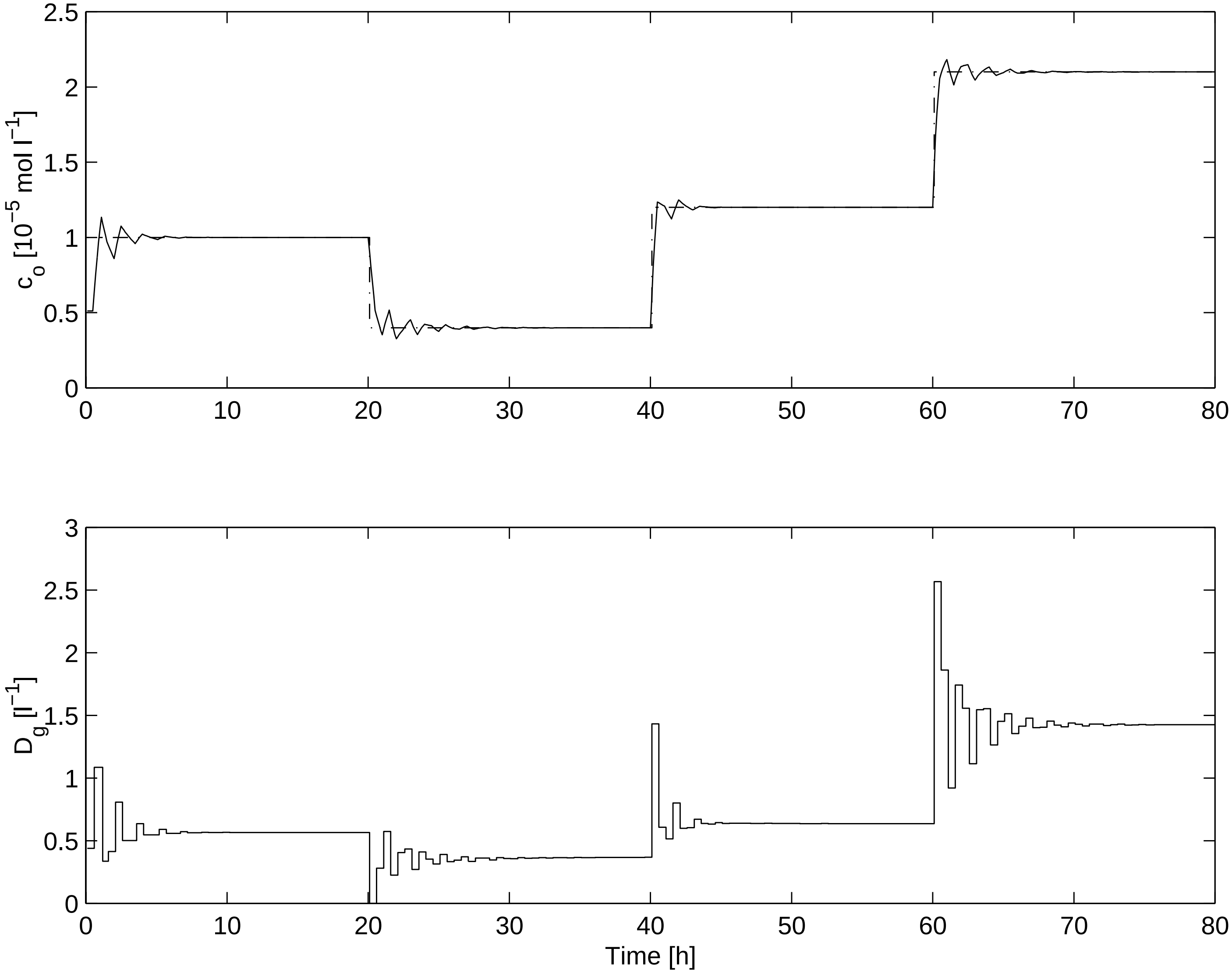
- Input layer(6): $[y(t), y(t-1), y(t-2), u(t), u(t-1), u(t-2)]$,
- two hidden layers(5, 3)
- output layer(1)

Cost function: quadratic

$$J = \sum_{j=1}^{P} (y^*(t+j) - y(t+j))^2 + \lambda \Delta u^2(t+j-1)$$

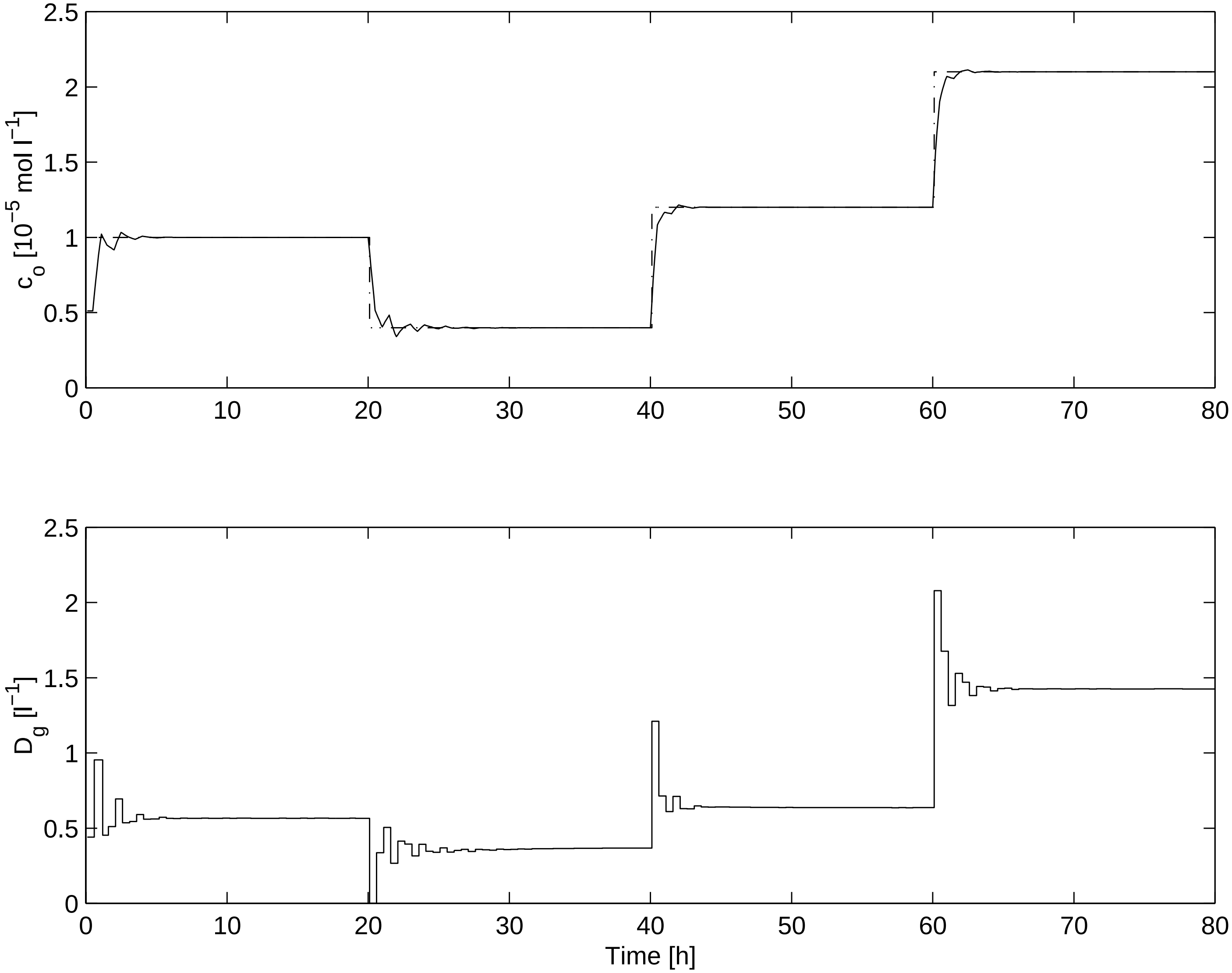
IDP Parameters: $P = 8$, $M = 8$, $N = 10$, $r^1 = 3$, $\varphi = 0.8$, $n = 3$.

Simulation Results



Fastest control, $\lambda = 0$

Simulation Results



Reduced oscillations, $\lambda = 0.1$

Conclusions

- Modified IDP: discrete-time, input-output models, receding horizon formulation
- Comparison of execution times : about 1% of the original IDP
- Comparison of control quality: similar behaviour of both manipulated and controlled variables