ProSafe

Smart Integration of Process Systems Engineering & Machine Learning for Improved Process Safety in Process Industries – Doctoral Network

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Learning-based Health-Aware Control for Improved Process Safety

A Case Study of Oil-Gas Wells

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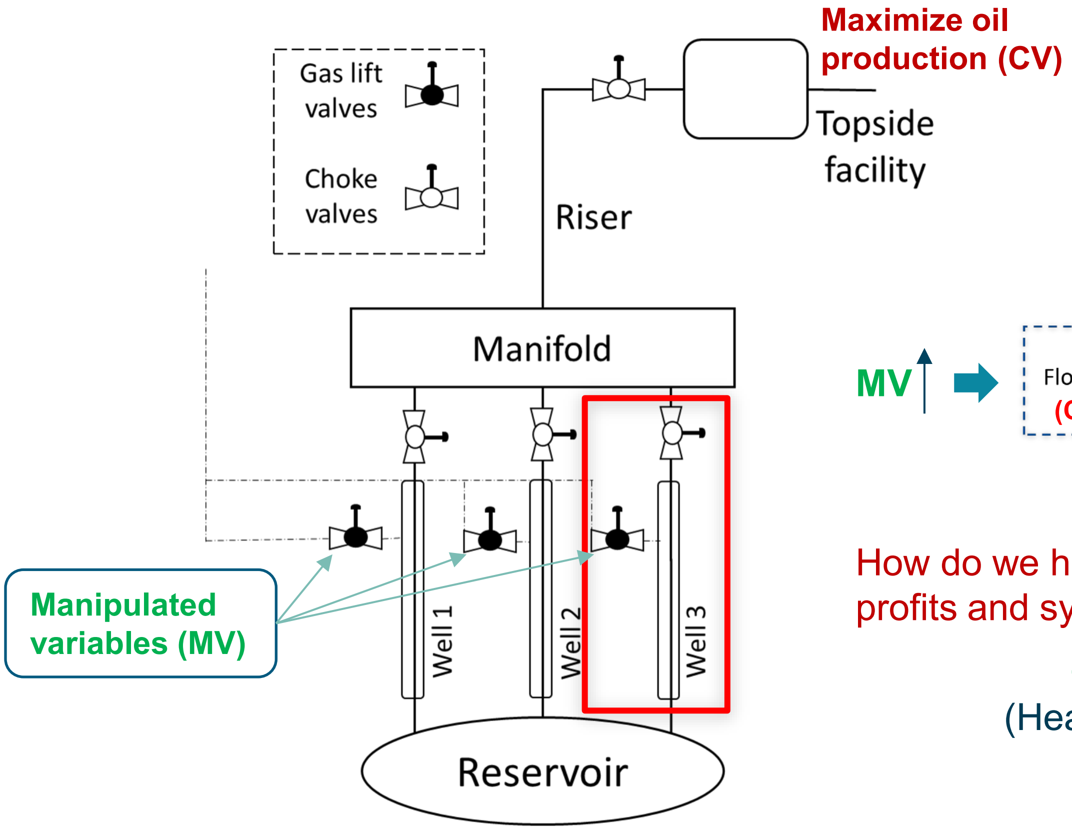
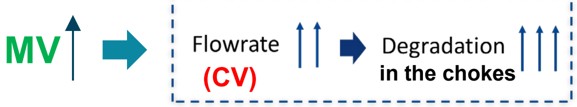
Case Study: Gas Well Networks

Motivation: Profit-Health Trade-Off





How do we have a nice trade-off between profits and system health?

Optimal Control

(Health-Aware eNMPC)

HAC Formulation

Maximize oil production in a planned time subject to process and health constraints

$$V_N(\hat{x}) = \max_{u,x} \sum_{k=t_0}^{N-1} w_{po,k} - 0.5\Delta u_k{}^T R \Delta u_k - \rho S_k$$

Subject to :

$$\begin{array}{cc}
[x_{t_0}, u_{t_0-1}] = [\hat{x}, \hat{u}] & \\
x_{k+1} = F_1(x_k, u_k) & k \in [t_0, t_0 + N - 1] \\
0 = F_2(z_k, u_k) & k \in [t_0, t_0 + N - 1] \\
y_k = C(x_k, u_k) & k \in [t_0, t_0 + N - 1] \\
G(x_k, u_k) - s_k \leq 0 & k \in [t_0, t_0 + N - 1] \\
s_k \geq 0 & k \in [t_0, t_0 + N - 1] \\
u_{min} \leq u_k \leq u_{max} & k \in [t_0, t_0 + N - 1] \\
\Delta u_k = u_k - u_{k-1} & k \in [t_0, t_0 + N_c - 1] \\
|\Delta u_k| \leq \Delta u_{max} & k \in [t_0, t_0 + N_c - 1] \\
\Delta u_k = 0 & k \in [t_0 + N_c, t_0 + N - 1]
\end{array}$$

Models (DAEs)

Gas-lift model (steady state)

Phase balance model

$$\begin{bmatrix}0\\0\\0\end{bmatrix} = \begin{aligned} \dot{m}_{ga} &= w_{gl} - w_{iv}, \\ \dot{m}_{gt} &= w_{iv} - w_{pg} + w_{rg}, \\ \dot{m}_{ot} &= w_{ro} - w_{po}, \end{aligned}$$

Density model

$$\rho_a = \frac{M_w p_a}{T_a R},$$

$$\rho_w = \frac{m_{gt} + m_{ot} - \rho_o L_r A_r}{L_w A_w},$$

Flow model

$$w_{iv} = C_{iv}\sqrt{\rho_a max(0, p_{ai} - p_{wi})},$$

$$w_{pc} = C_{pc}\sqrt{\rho_w max(0, p_{wh} - p_m)},$$

$$w_{pg} = \frac{m_{gt}}{m_{gt} + m_{ot}} w_{pc},$$

$$w_{po} = \frac{m_{ot}}{m_{gt} + m_{ot}} w_{pc},$$

$$w_{ro} = PI(p_r - p_{bh}),$$

$$w_{rg} = GOR \cdot w_{ro},$$

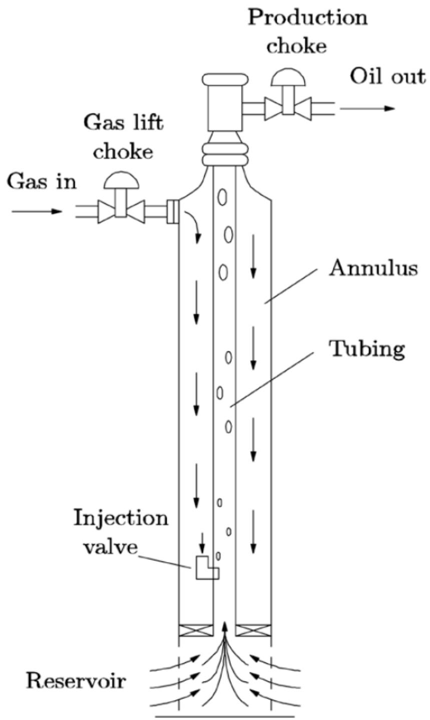
Pressure model

$$p_a = \left(\frac{T_a R}{V_a M_w} + \frac{g L_a}{L_a A_a}\right) m_{ga},$$

$$p_{wh} = \frac{T_w R}{M_w}\left(\frac{m_{gt}}{L_w A_w + L_r A_r - \frac{m_{ot}}{\rho_o}}\right),$$

$$p_{wi} = p_{wh} + \frac{g}{A_w L_w}(m_{ot} + m_{gt} - \rho_o L_r A_r) H_w,$$

$$p_{bh} = p_{wi} + \rho_w g H_r,$$



Erosion model

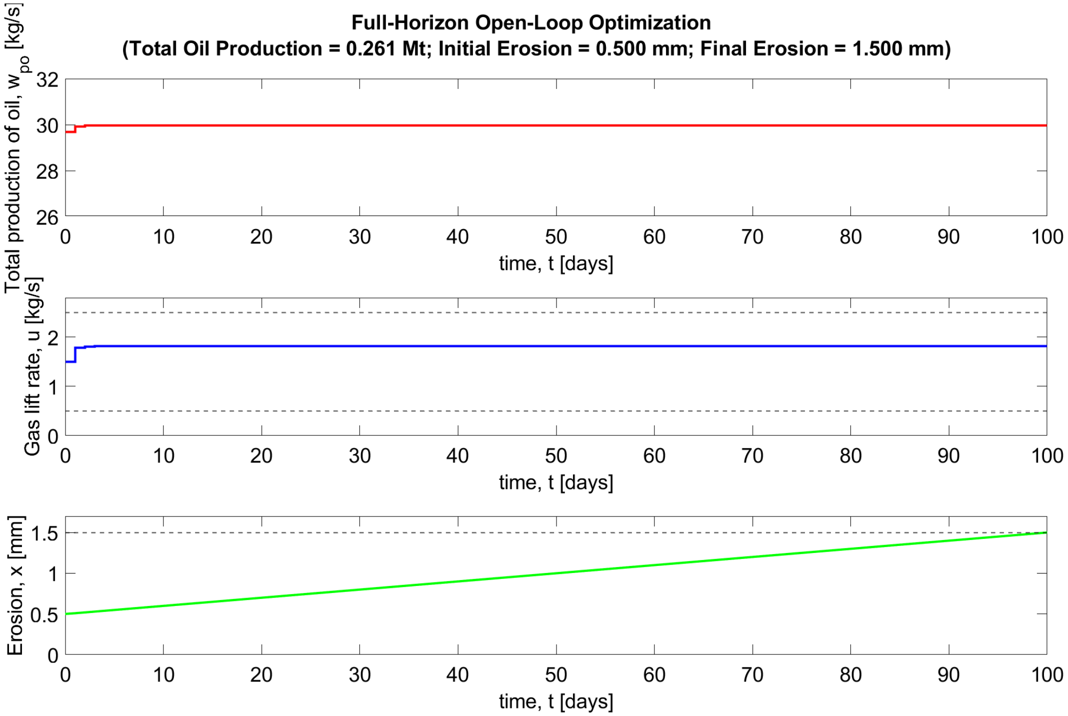
$$\dot{\epsilon} = \frac{K \cdot F(\alpha) \cdot U_p^n}{\rho_t \cdot A_t} \cdot G \cdot C_1 \cdot G_f \cdot \dot{m}_p \cdot C_{unit}$$

Open-Loop Optimization

CV

MV

HV



We want to achieve the same (or similar) performance FASTER (i.e. lower solve time) using ML models

Fast HACC: ADP-flavoured Health-Aware eNMPC

Fast HAC Formulation

Basic Idea

Optimize with a **very short horizon** while taking into account the long-term effects in the cost-to-go (CTG) – motivated by **Bellman's principle of optimality**, i.e.:

Needs to be known beforehand

Do

$$\hat{V}_N(\hat{x}) = \min_{u_0} \quad l_0(\hat{x}, u_0) + \boxed{\hat{V}_{N-1,\mu}(x_1)}, \quad x_1 = f(\hat{x}, u_0)$$

Instead of

$$V_N(\hat{x}) = \min_{u_0, u_1, \ldots, u_{N-1}} \quad \sum_{k=0}^{N-1} l_k(x_k, u_k)$$

Ways to learn the CTG term (optimal **value** function):

1. **(Approximate) Dynamic** Programming: CTG term approximated iteratively
2. **Learning-based MPC:** supervised learning of CTG labels

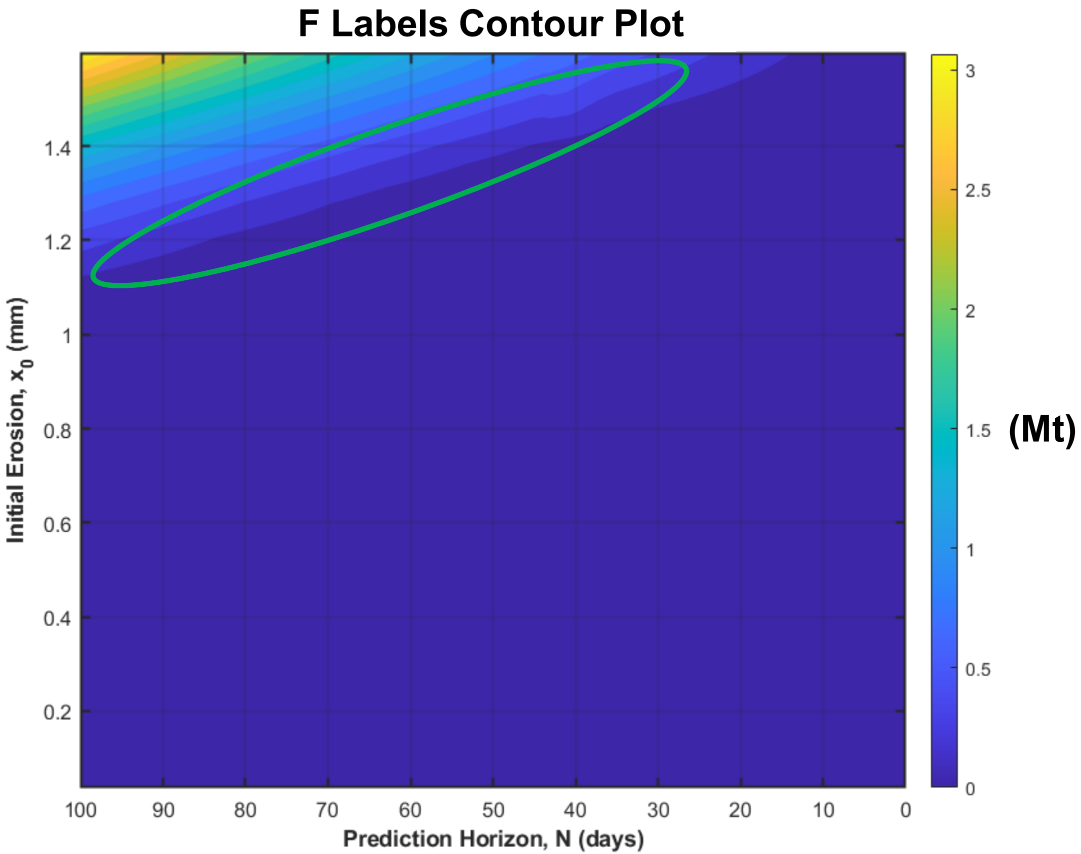
Algorithm for Creation of One-Step eNMPC

1. **Generate labels:**
   - Perform **full-horizon open-loop optimization** to obtain the optimal CTG values $V_N(\hat{x})$ for sampled *initial erosion values* $(\hat{x})$ and *prediction horizons* (N).
2. **Train a surrogate** (approximate) **model,** $\hat{V}_N(\hat{x})$:
   - Fit an **input-convex neural network (ICNN)** model to the training data
3. **Deploy one-step eNMPC:**
   - Solve the one eNMPC with $\hat{V}_{N-1,\mu}(x_1)$ as the terminal cost.

NB: To better handle future constraints (feasibility), the CTG surrogate is split into two, i.e.:

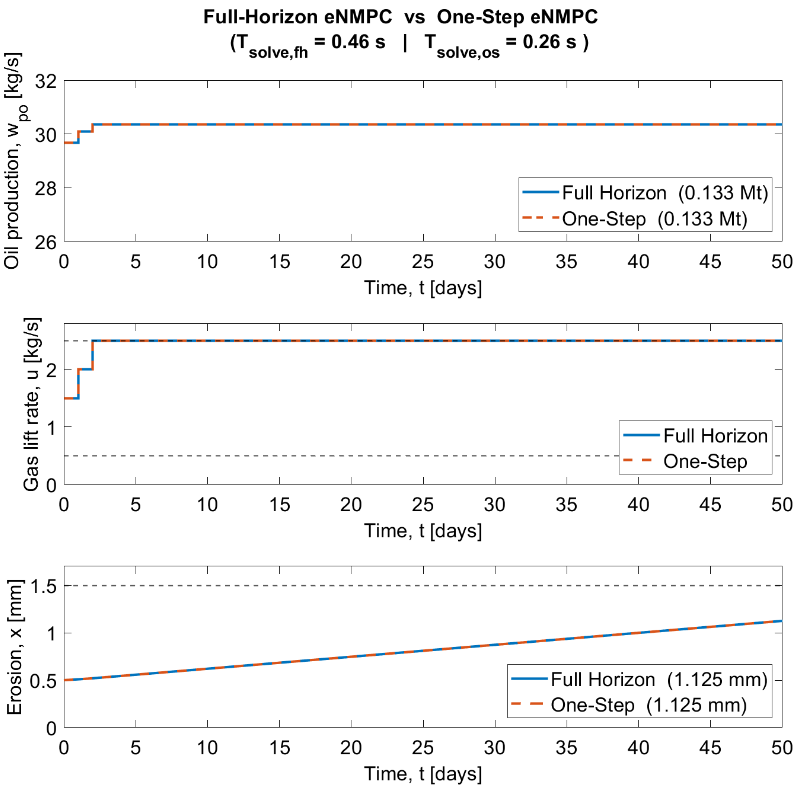
$$\hat{V}_{N-1,\mu}(x_1) = \underbrace{\hat{V}_{N-1}(x_1)}_{\textbf{Optimality}} + \underbrace{\mu\hat{F}_{N-1}(x_1)}_{\textbf{Feasibility}}$$

Feasibility Data Visualization

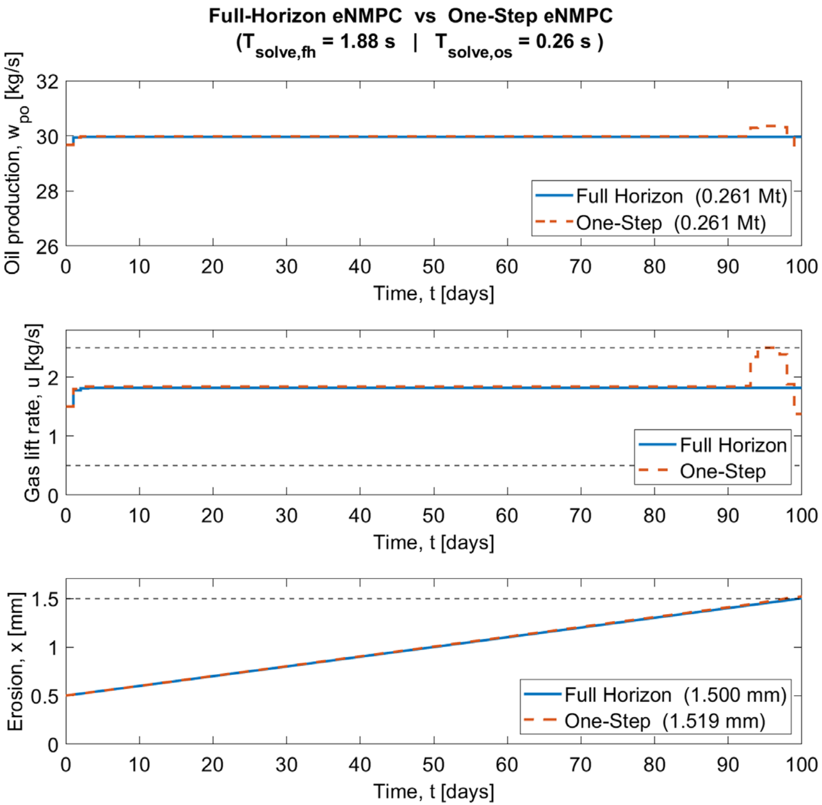


Closed-Loop Implementation*

Feasible Region



Boundary Region



***no plant-model mismatch**

Remarks on Oil Well Case Study

- The one-step controller behaves exactly (or close) to the full-horizon controller in the **feasible region**:
  - Need better **F surrogate** performance at the boundary of infeasibility (around & at **kink**).

Ideas	**Action**	**Done or not?**	**Improvement?**
Focused training for F surrogate – better local prediction	Weighted MSE	✓	No
Learn 1st derivative information better to capture the 'kink' Add a regularization term on gradients during training	Gradient targets from data	✓	No
	Using dx as a 3rd feature	✓	No
	Using costates as gradient targets since $(\lambda^*(t) = \nabla_x V(x^*(t), t))$	In progress	-
Alternative models and formulations	Reformulate as MILP: a ReLU ANN	✗	-
	Use RNNs as a surrogate	✗	-

Conclusions & Outlook

- A learned ICNN cost-to-go can reproduce long-horizon eNMPC behavior in the feasible operating region.
- Near active health constraints, performance depends strongly on the (feasibility) surrogate's accuracy and sensitivity around the feasible set boundary.
- Future work will focus on constraint-aware training, sensitivity matching, and extension to MIMO uncertain systems.

Thank you for your attention!