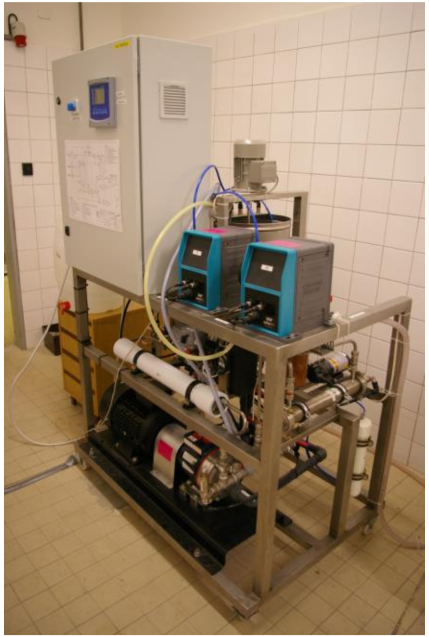
Experimental Real Time Optimization of a Continuous Membrane Separation Plant

Anwesh Reddy Gottu Mukkula[1], Petra Valiauga[2], Miroslav Fikar[2], Radoslav Paulen[2], Sebastian Engell[1]

[1] Process Dynamics and Operations Group, Department of Biochemical and Chemical Engineering, Technical University of Dortmund, Germany
[2] Faculty of Chemical and Food Technology, Slovak University of Technology in Bratislava, Slovakia

Motivation



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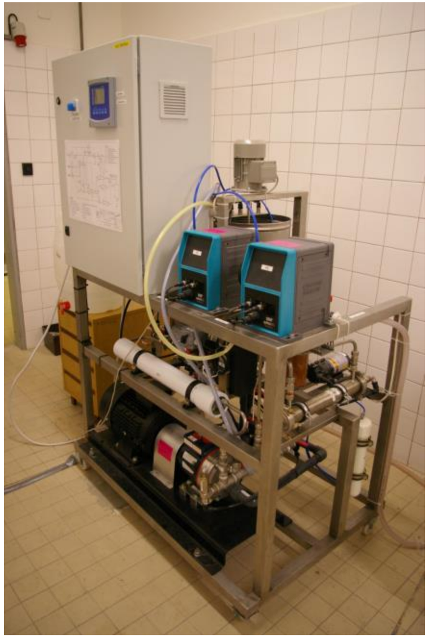

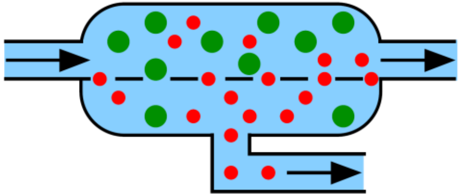

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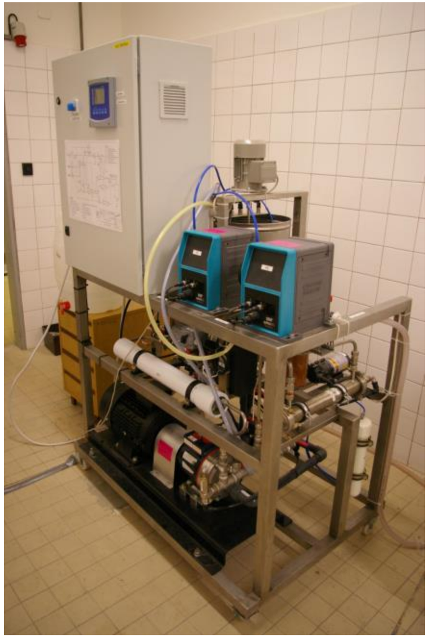

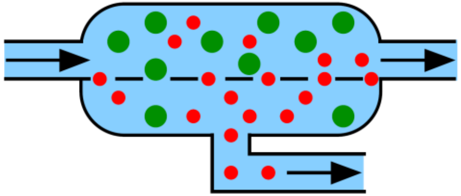

Goal

- Identify the optimal operating input for a nanofiltration membrane separation process
- Process and productivity constraints have to be taken into account

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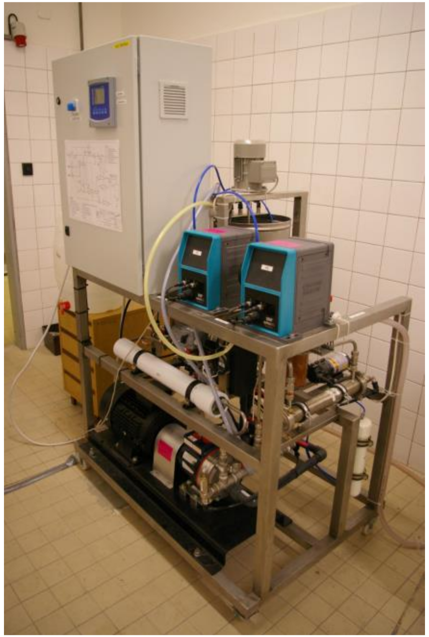

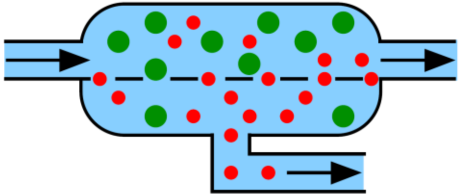

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$$\text{s.t. } \mathbf{y} = \mathbf{f}_p(\mathbf{u})$$

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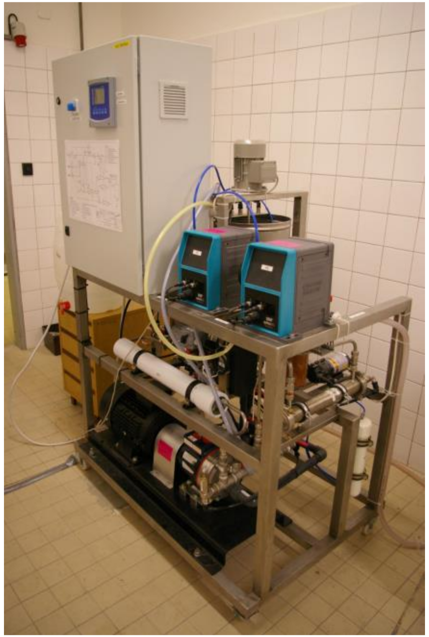

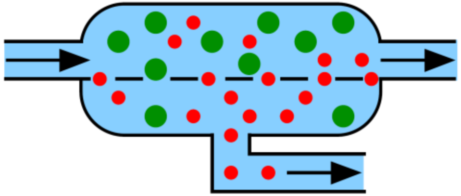

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- Unknown process model

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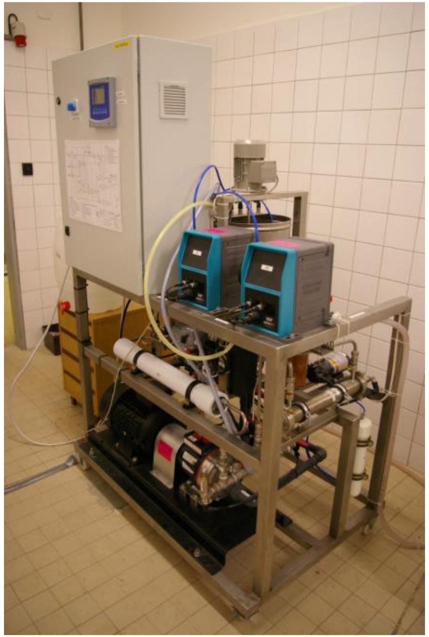

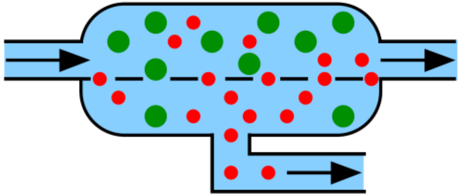

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Proposed solution

- Real-time optimization methods

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Real-time optimization

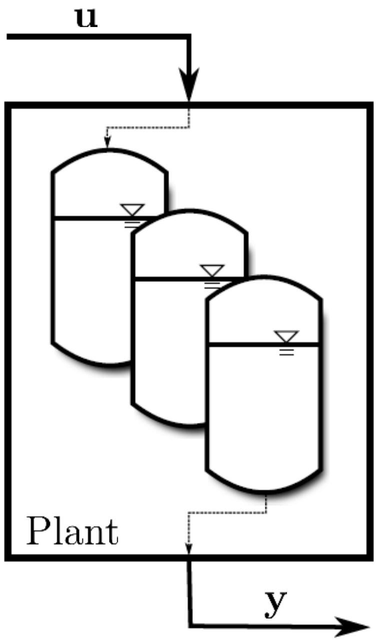

Figure: Illustration of a general plant.

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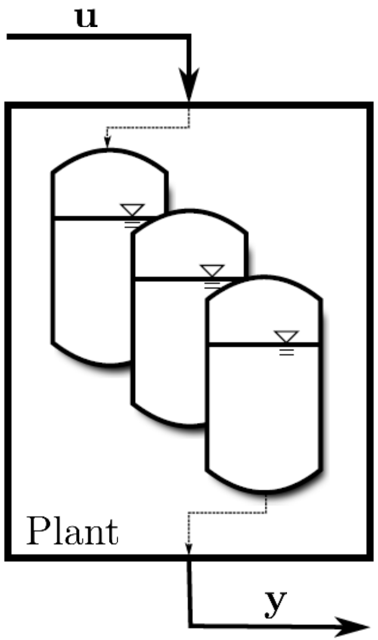

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Model:

$$\mathbf{u}_m^* = \min_{\mathbf{u}} \mathcal{J}_m(\hat{\mathbf{y}}, \mathbf{u})$$
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$$\mathbf{u}_m^* \neq \mathbf{u}_p^*$$

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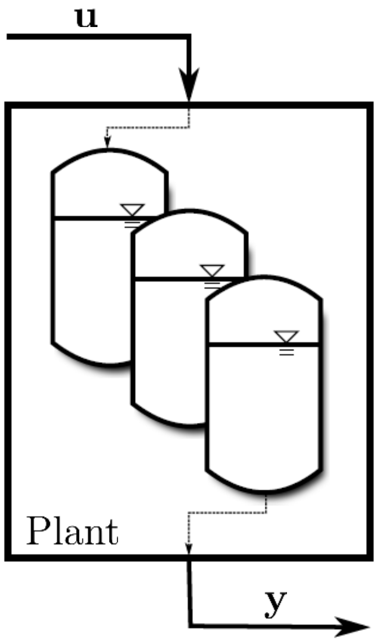

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RTO method

- Modifier adaptation with quadratic approximation (MAWQA)

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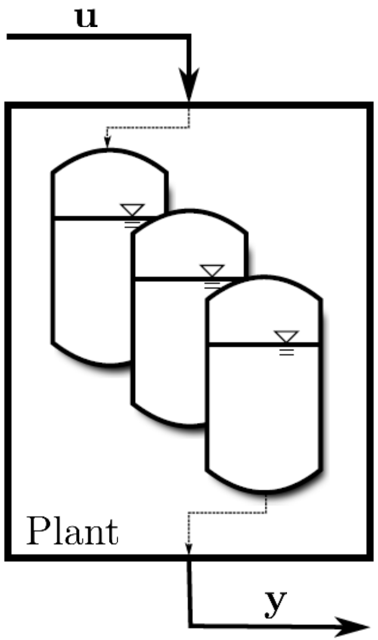

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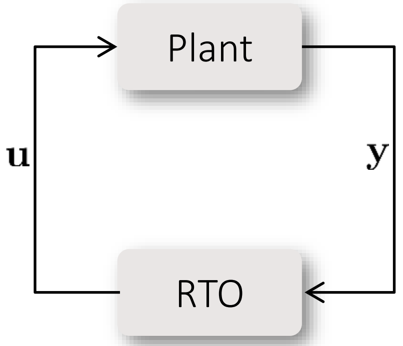

Modifier adaptation (MA)

Model-based optimization

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$$\hat{\mathbf{u}}_m^{*k+1} = \min_{\mathbf{u}} \mathcal{J}_m^{ad,k}(\hat{\mathbf{y}}, \mathbf{u})$$
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Modified objective function and constraints:

$$\mathcal{J}_m^{ad,k}(\mathbf{x}, \mathbf{u}) = \mathcal{J}_m(\hat{\mathbf{y}}, \mathbf{u}) + (\nabla \mathcal{J}_p^k - \nabla \mathcal{J}_m^k)^T (\mathbf{u} - \mathbf{u}^k)$$
$$\mathbf{g}_m^{ad,k}(\mathbf{x}, \mathbf{u}) = \mathbf{g}_m(\mathbf{x}, \mathbf{u}) + (\mathbf{g}_p^k - \mathbf{g}_m^k) + (\nabla \mathbf{g}_p^k - \nabla \mathbf{g}_m^k)^T (\mathbf{u} - \mathbf{u}^k)$$

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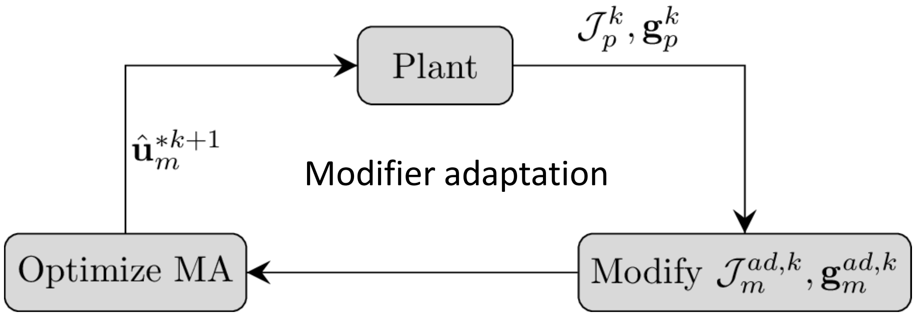

Modifier adaptation with quadratic approximation (MAWQA)[1]

Quadratic approximation (QA)

$$\mathcal{Q}(\mathcal{P}, \mathbf{u}) = \sum_{i=1}^{n_u} \sum_{j=1}^{i} a_{i,j} u_i u_j + \sum_{i=1}^{n_u} b_i u_i + c$$

$$\mathcal{P} = \{a_{1,1}, \cdots, a_{n_u,n_u}, b_1, \cdots, b_{n_u}, c\}$$

- Screening algorithm to choose points for QA

Finite differences

- Used for gradient approximation when not enough points are available for fitting a quadratic function
- When number of available points are less than $\frac{(n_u+1)(n_u+2)}{2}$

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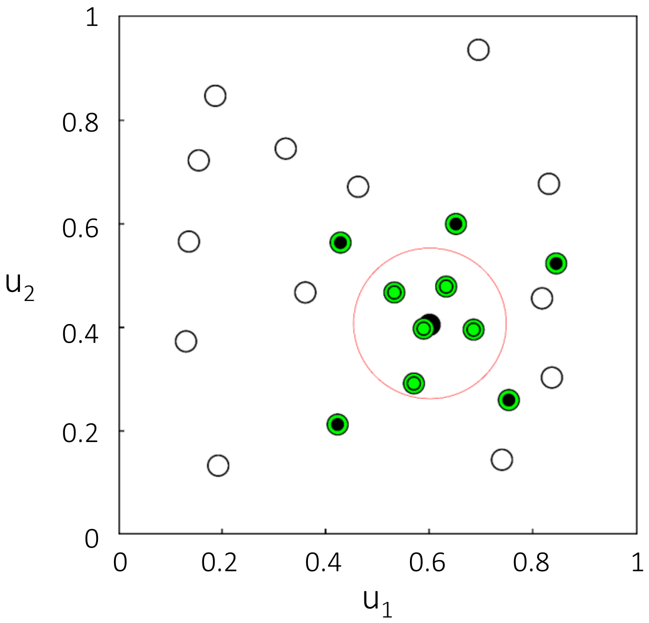

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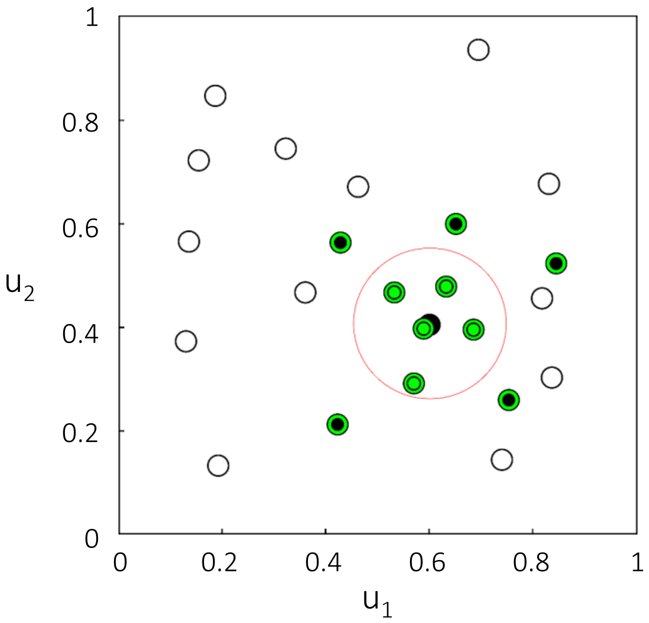
- Screening algorithm to choose points for QA → **Criticality Check**



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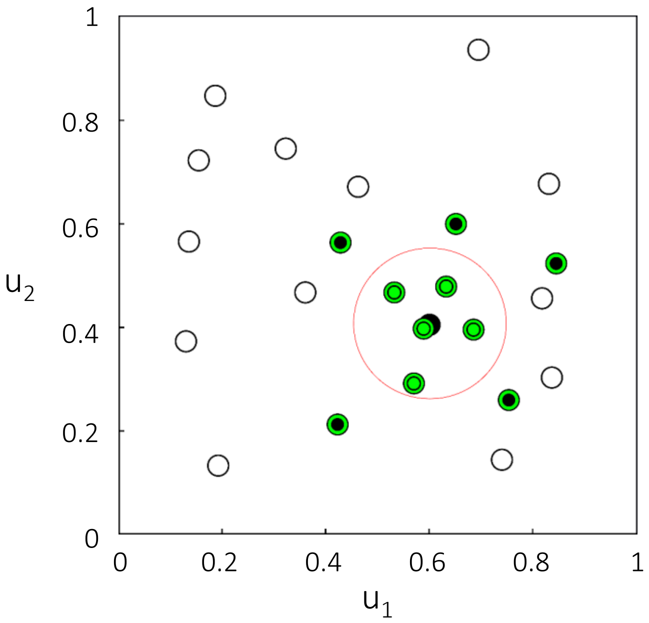

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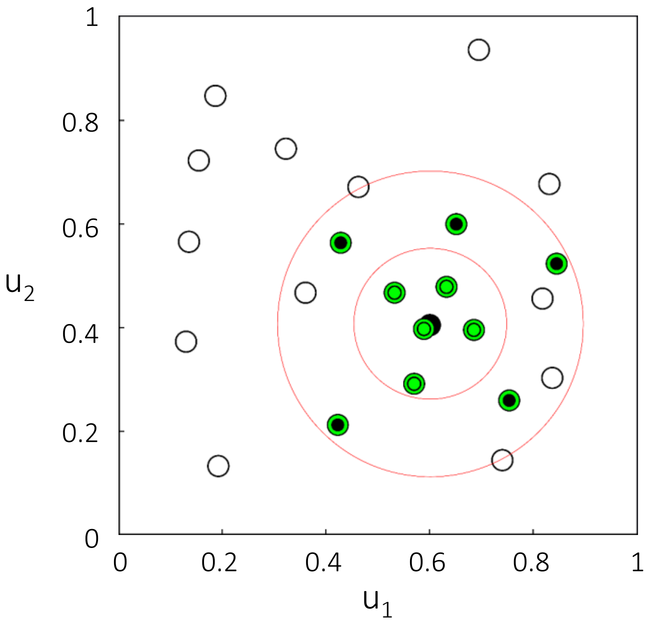

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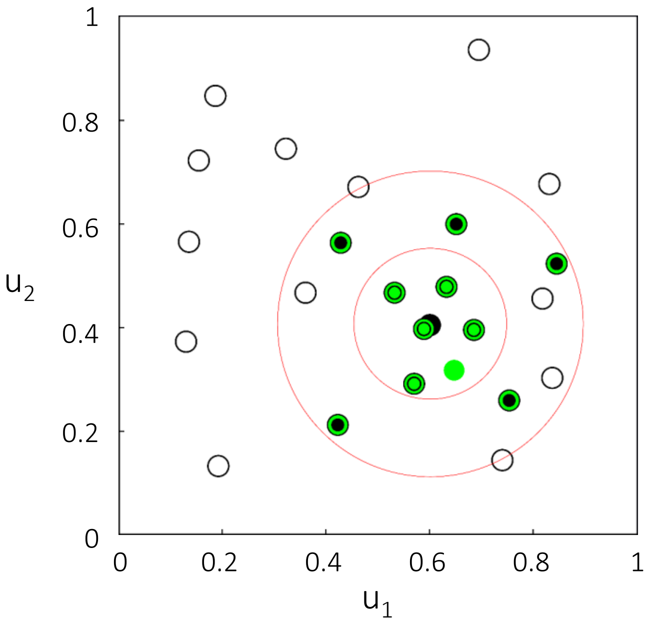

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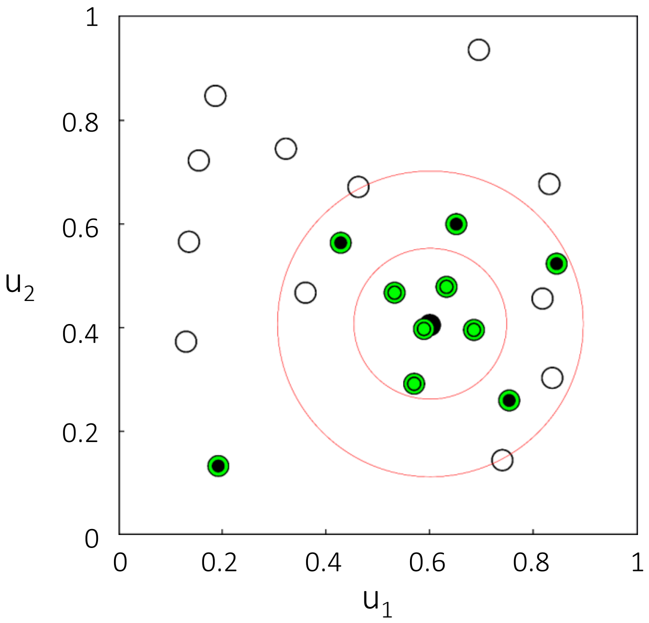

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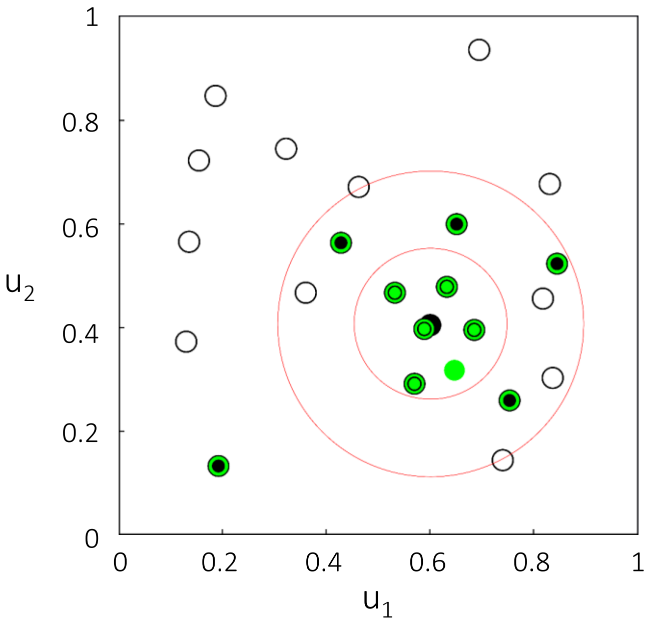

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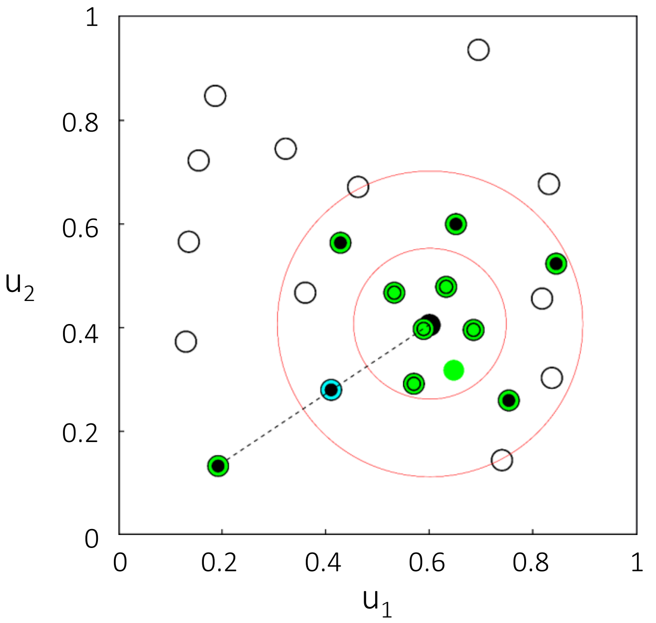

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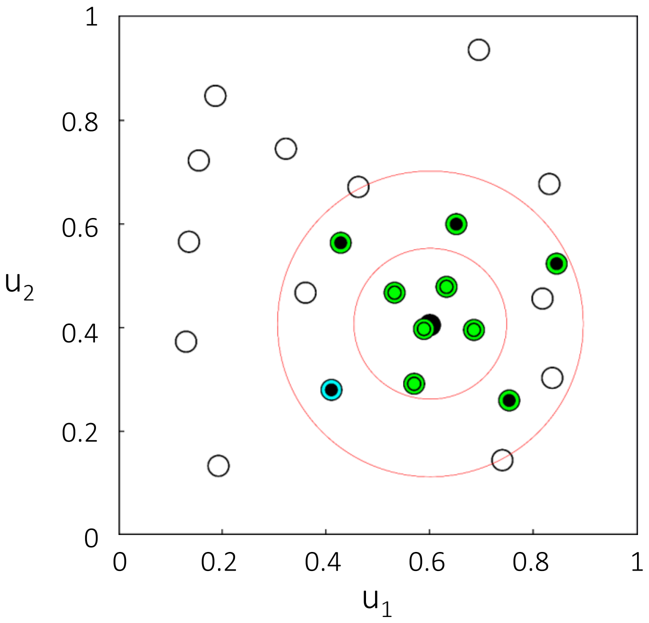

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Membrane separation process

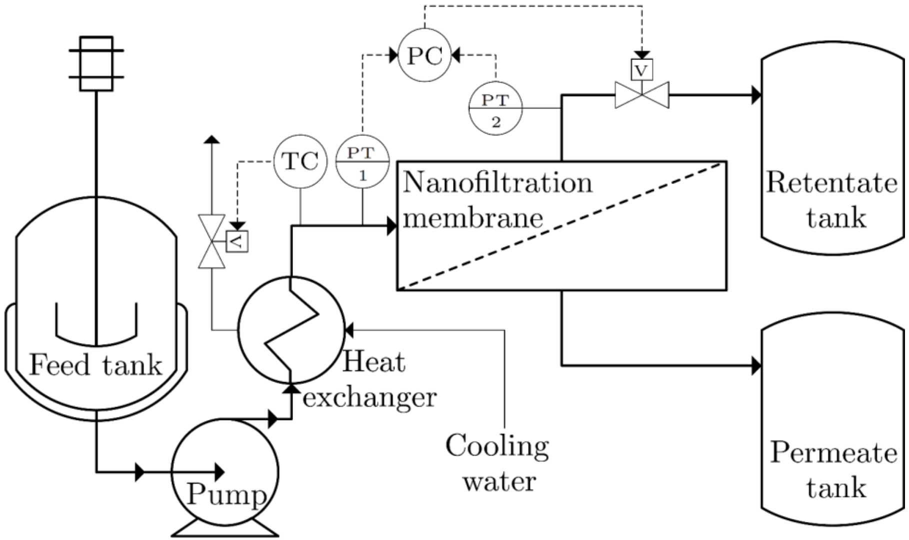

Figure: Illustration of the process flow diagram of the continuously operated membrane separation process.

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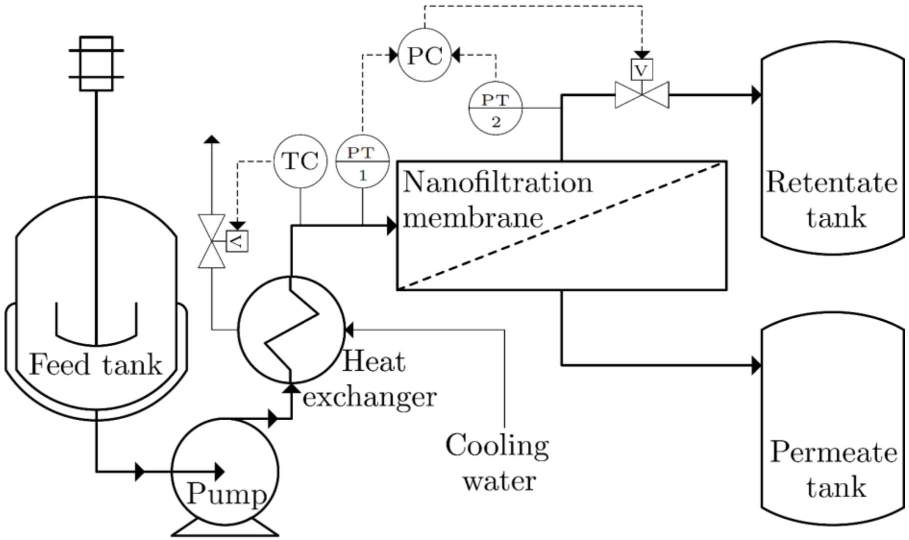

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$$\max_{\boldsymbol{u}=\{\Delta P, T\}} \quad \dot{V}_p \kappa_p - 50\Delta P^2 - 5\Delta P(T_{\text{amb}} - T)$$

$$\text{s.t. nominal model,}$$

$$18 - \dot{V}_p \leq 0,$$

$$4 \leq \Delta P \leq 22,$$

$$20 \leq T \leq 30.$$

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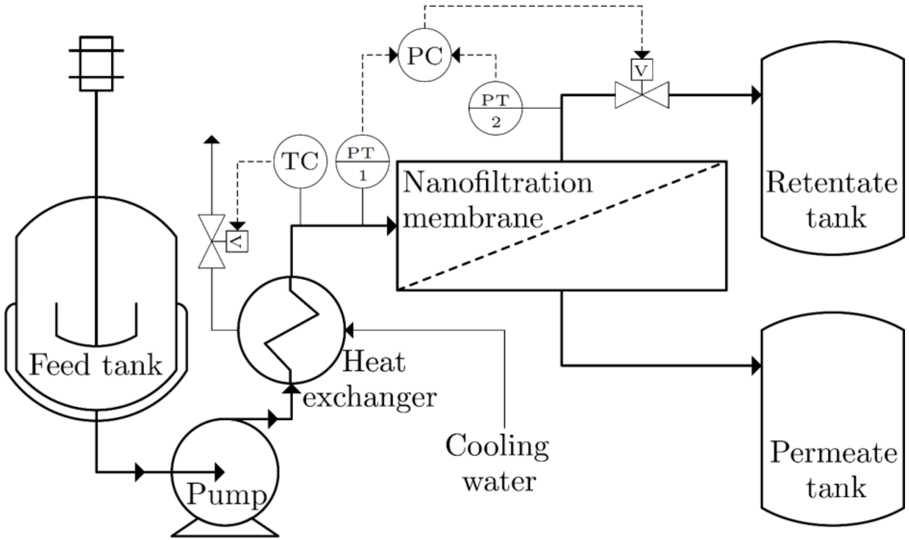
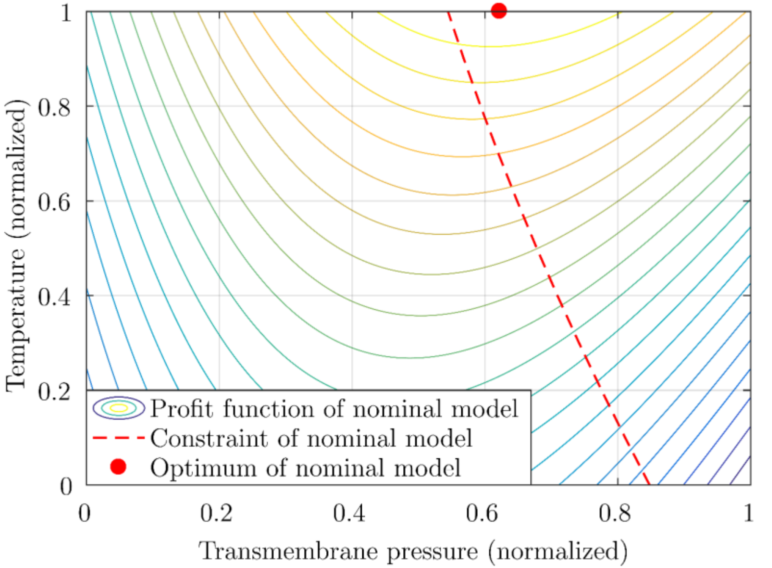


Figure: Illustration of the process flow diagram of the continuously operated membrane separation process.



$$\max_{\boldsymbol{u}=\{\Delta P, T\}} \quad \dot{V}_p \kappa_p - 50\Delta P^2 - 5\Delta P(T_{\text{amb}} - T)$$

$$\text{s.t. nominal model,}$$

$$18 - \dot{V}_p \leq 0,$$

$$4 \leq \Delta P \leq 22,$$

$$20 \leq T \leq 30.$$

Gottu Mukkula, A.R., et al., Experimental Real Time Optimization of a Continuous Membrane Separation Plant
21st IFAC World Congress, July 12th-17th, 2020

MAWQA Experiment result without productivity constraint

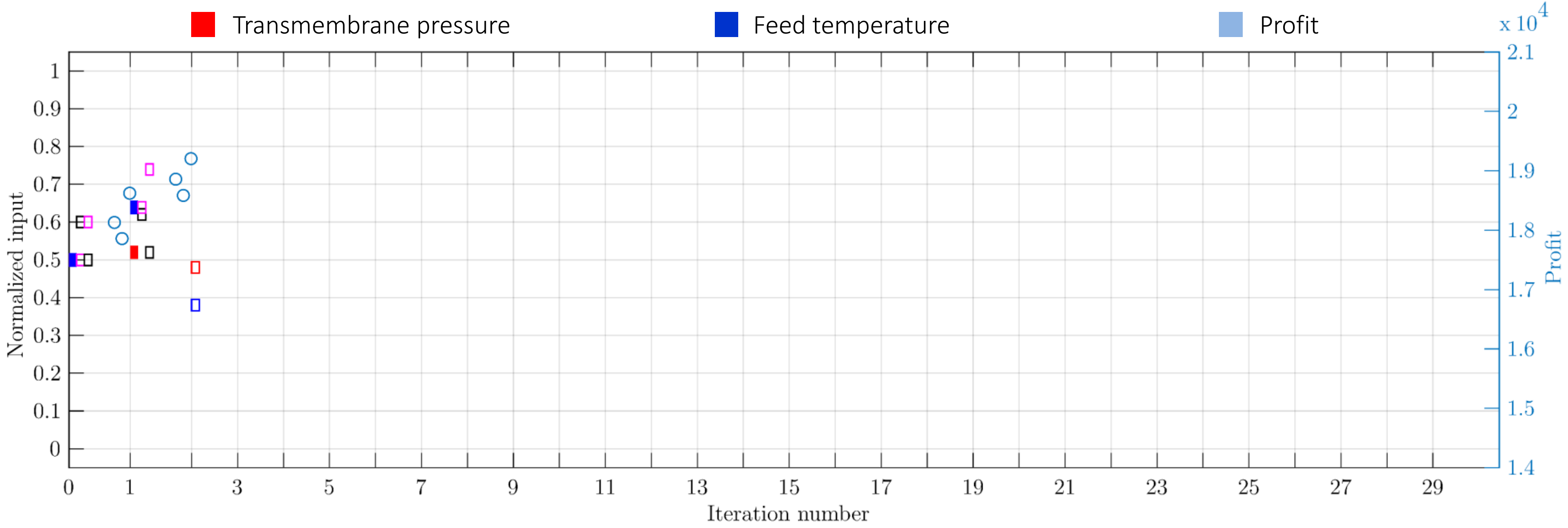
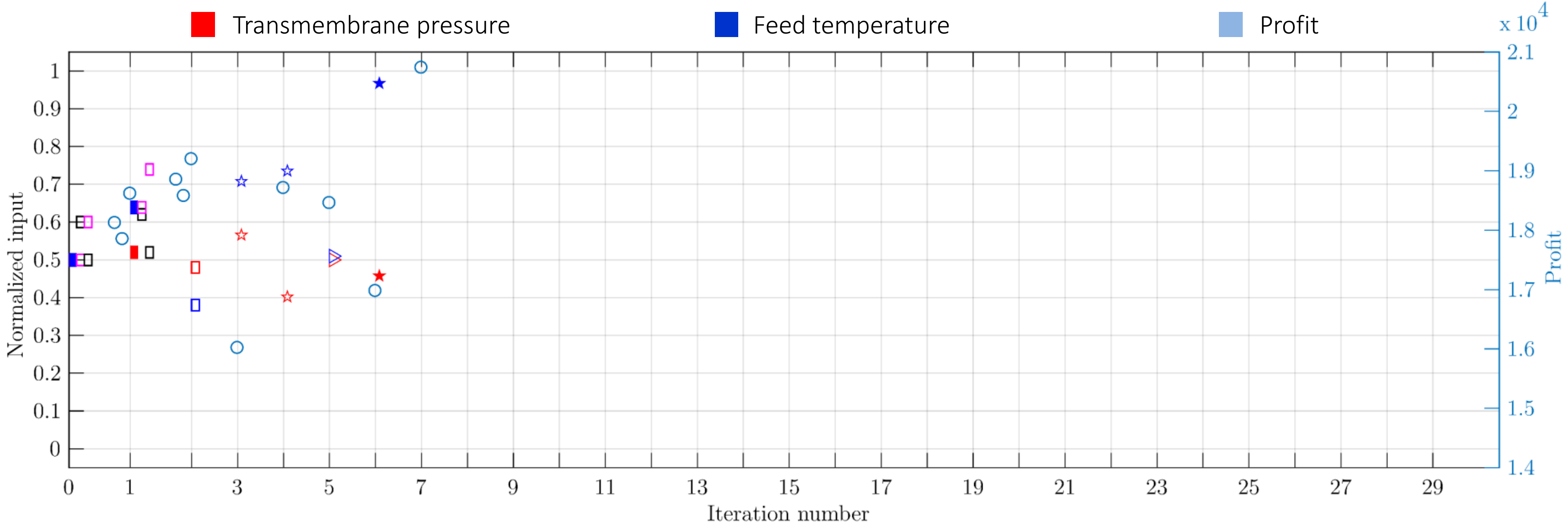


Figure: Experimental results for the unconstrained case: Evolution of the inputs (normalized) transmembrane pressure, temperature and the profit function obtained using process measurements. The tuning parameters γ, Δu, Δh and δ were set to 3.0, 0.1, 0.1 and 0.1, respectively.

MAWQA Experiment result without productivity constraint



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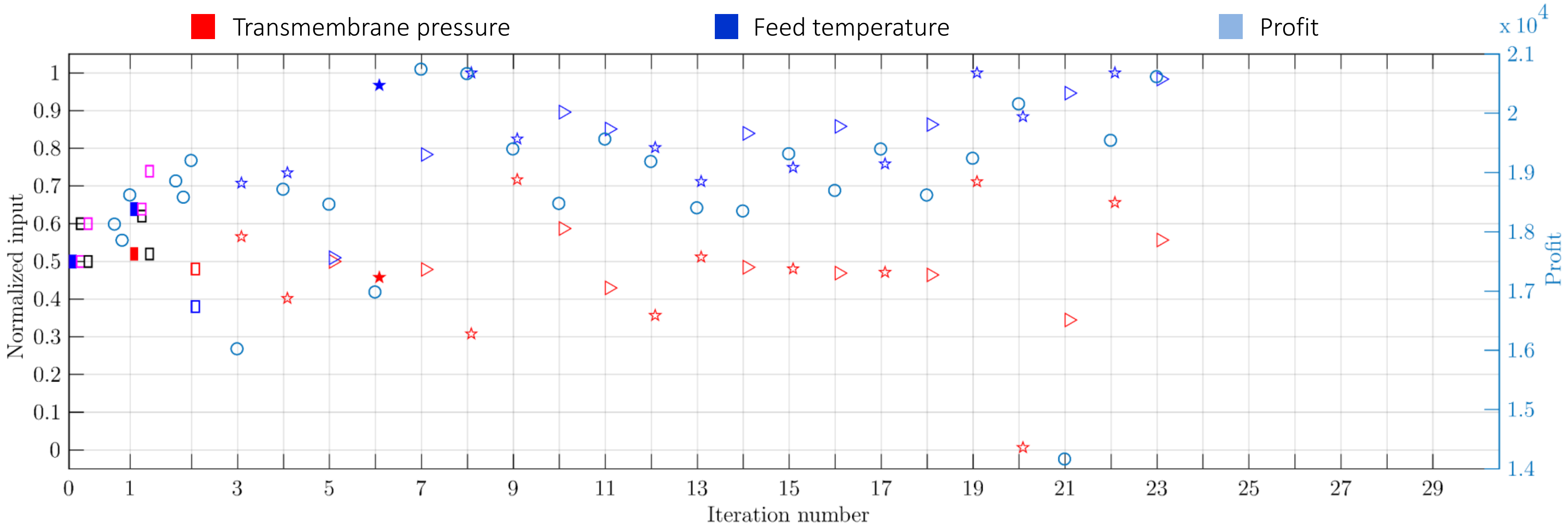
MAWQA Experiment result without productivity constraint



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MAWQA Experiment result without productivity constraint

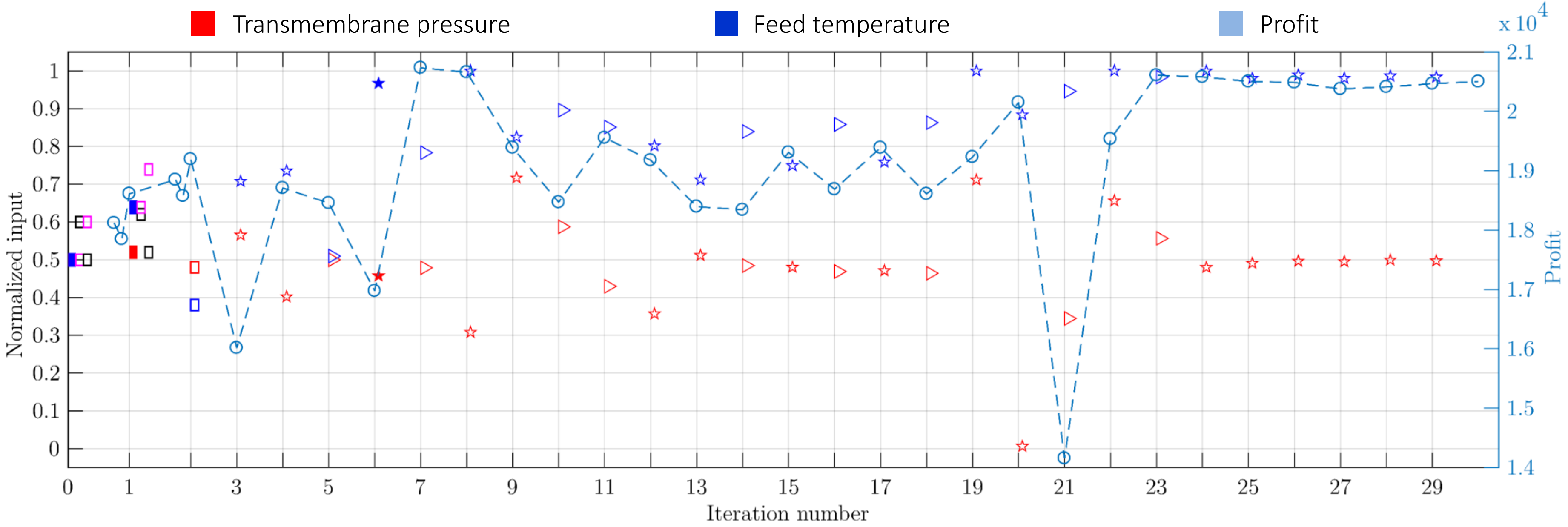


Figure: Experimental results for the unconstrained case: Evolution of the inputs (normalized) transmembrane pressure, temperature and the profit function obtained using process measurements. The tuning parameters γ, Δu, Δh and δ were set to 3.0, 0.1, 0.1 and 0.1, respectively.

MAWQA Experiment result with productivity constraint

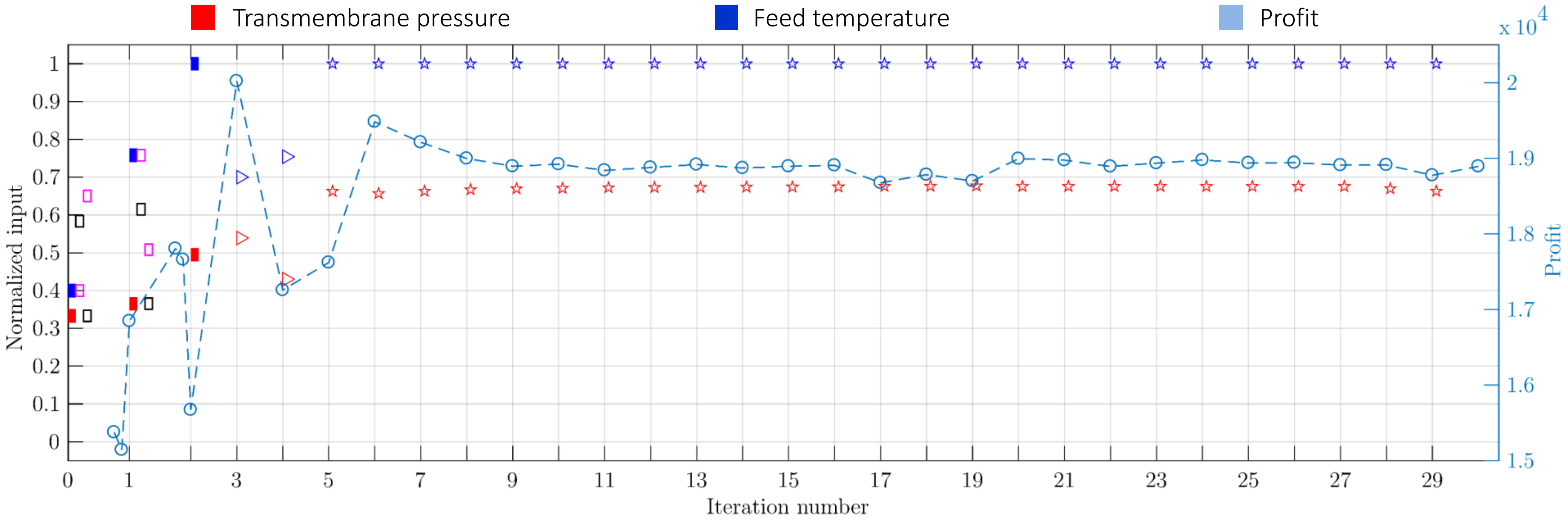
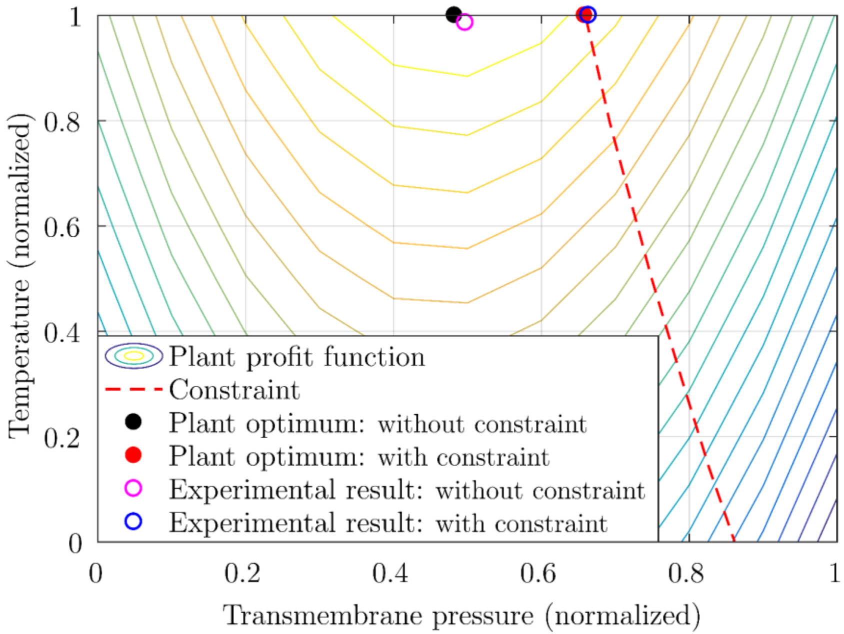


Figure: Experimental results for the constrained case: Evolution of the inputs (normalized) transmembrane pressure, temperature and the profit function obtained using process measurements. The values of the tuning parameters γ, Δu, Δh and δ used in the MAWQA scheme are set to 3.0, 0.25, 0.25 and 0.25.

Validation of experiment results



Top figure: Contour plot of the profit function of the nominal models and of the plant, its optimum and the optimum identified by the MAWQA experiments for both the constrained and the unconstrained cases.

Summary & Outlook

- We reported the development of an online real-time optimization solution (MAWQA) for the optimal operation of a continuously operated membrane plant with a nanofiltration membrane.
- Two experiments, one without constraints and another one with a productivity constraint were performed.
- In both experiments, the MAWQA scheme converged to an input close to the plant optimum that is predicted by the surrogate model for a large data set.
- The experiments validated that the combination of the plant measurements with MAWQA can drive a real plant to an optimal operation despite plant-model mismatch
- In our future work, we will focus on reducing the inefficient input moves and on developing a standardized approach for choosing the tuning parameters.

Thank you

anweshreddy.gottumukkula@tu-dortmund.de

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