Intuitive perturbation-based optimization applied to a dividing-wall distillation column

Nordic Process Control Workshop 2026

Mark Haring, Leontine Aarnoudse, and Ivar J. Halvorsen

Context: optimization of uncertain processes

© Chad Teer / CC BY 2.0 / unchanged

© Neil Maw / CC BY-SA 3.0 / unchanged

Feed variations

Upstream variations

Limited understanding of process

Recycling of waste products

Limited measurements

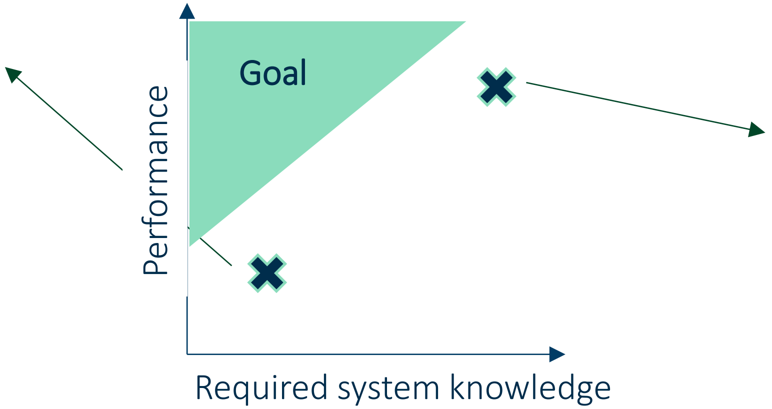
Changes in (unknown) environment

© Hans Hillewaert / CC BY-SA 4.0

Highly uncertain and time-varying processes → often suboptimal operation

Controlling processes with large uncertainties

Human operators
• Trial and error • Observations • Procedures • Experience



Automated solutions
• Model-based: uncertainty leads to conservative control • Data-driven: data gets less relevant over time • Feedback: requires known setpoints

- Model or data knowledge needed for existing automated solutions can be difficult and expensive to obtain and update
- Many highly uncertain, time-varying processes are manually controlled by human operators
  - Operation is generally suboptimal given amount of available knowledge

Human control with large uncertainties

- Why are human operators controlling process suboptimally?
  - Trial and error is necessary, but implementation is poor

- Reasons why trial and error is implemented suboptimally:
  - Small changes to process parameters are not implemented to prioritize steadiness
  - Tight collaboration between operators is lacking
    - for slow process responses that span multiple work shifts
  - Clear, common understanding of optimality is missing

- Solution: automate trial and error

Efficient optimization of uncertain systems

Requirements for automated solution	
Performance	1) Find and track a time-varying optimum 2) Use very limited process knowledge
Long-term results	3) Deal with data that gets less relevant over time
Operator involvement	4) Easy implementation in ongoing process 5) Limited disruption of ongoing process
Validation	6) Demonstrate feasibility on a real system

Solution direction: perturbation-based optimization


Contents lists available at ScienceDirect

Journal of Process Control

journal homepage: www.elsevier.com/locate/jprocont

A real-time cost optimization of two-section oven system with discrete gradient extremum seeking control: An experimental study in iron and steel industry

Süleyman Yilmaz [a,*], Murat Furat [b]


Available online at www.sciencedirect.com

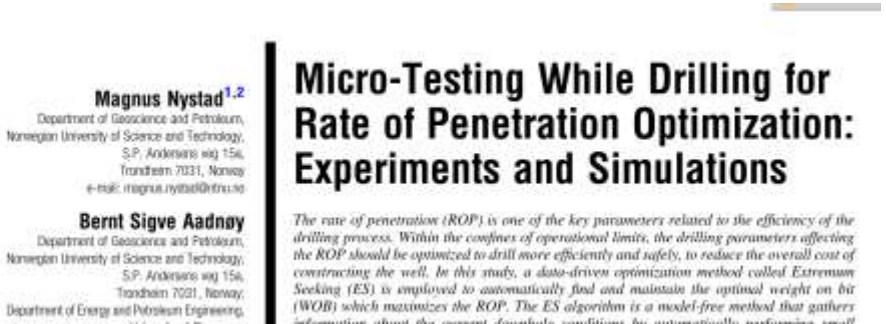
ScienceDirect

IFAC PapersOnLine 55-7 (2022) 137–142

Implementation of Extremum Seeking Control in an Experimental Lab-Rig ⋆

Jose Matias * Frida Bakken Myrvang * Johannes Jäschke *

* Chemical Engineering Department, Norwegian University of Science and Technology, Sem Sælandsvei 4, Kjemiblokk 5, Trondheim, Norway


Magnus Nystad [1,2]

Department of Geoscience and Petroleum, Norwegian University of Science and Technology, S.P. Andersens veg 15a, Trondheim 7031, Norway

Bernt Sigve Aadnøy

Department of Geoscience and Petroleum, Norwegian University of Science and Technology, S.P. Andersens veg 15a, Trondheim 7031, Norway

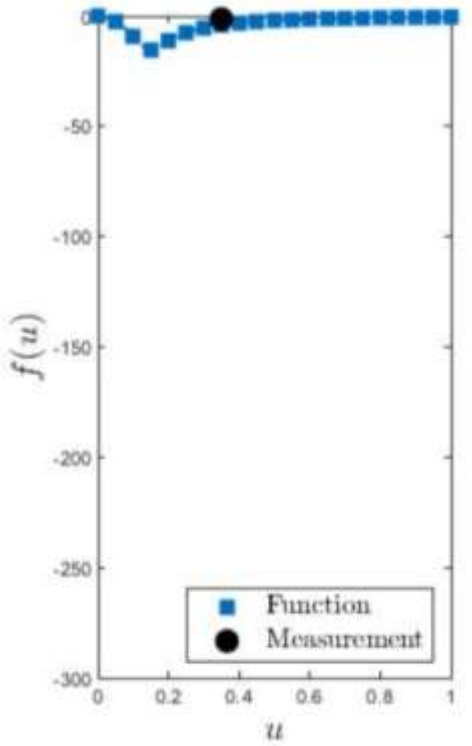
Micro-Testing While Drilling for Rate of Penetration Optimization: Experiments and Simulations

The rate of penetration (ROP) is one of the key parameters related to the efficiency of the drilling process. Within the confines of operational limits, the drilling parameters affecting the ROP should be optimized to drill more efficiently and safely, to reduce the overall cost of constructing the well. In this study, a data-driven optimization method called Extremum Seeking (ES) is employed to automatically find and maintain the optimal weight on bit (WOB) which maximizes the ROP. The ES algorithm is a model-free method that gathers

Perturb and observe

Perturb and observe

Change input in one direction until performance gets worse, then change direction

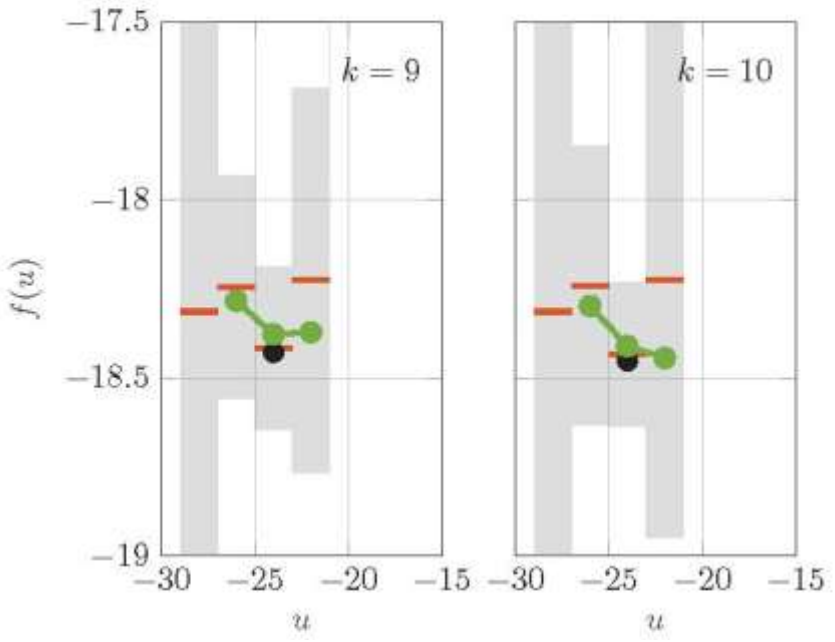


Limitations:

- Keeps perturbing after optimum is found
- Forgets previous measurements immediately
- Sensitive to noise

Uncertainty-based perturb and observe

Uncertainty-based perturb and observe



current measurement
selection next input
estimated value
uncertainty

Main idea:

- Trial and error leads to estimate of optimum location
- Model measurement noise and increase uncertainty over time
- Exploration/exploitation trade-off: only perturb when uncertainty about current location of optimum is high
- Implementation: pick the lowest point as the next input

Uncertainty-based perturb and observe: modeling

SINTEF

Current measurement

$$y_k = f_k(u_k) + \rho\varepsilon_k$$

output, function value, input, noise

Older measurements ($k \geq j$)

$$f_k\left(u^{(i)}\right) = y_j - \frac{\rho}{\lambda^{k-j}}\varepsilon_k, \text{ for } u_j = u^{(i)}$$

function value at input index i

forgetting factor increases over time ($\lambda \in (0,1)$)

Estimates from combining all data

$$\hat{f}_k\left(u^{(i)}\right) = \frac{\sum_{j\in J_k(u^{(i)})} \lambda^{2(k-j)}\, y_j}{\sum_{j\in J_k(u^{(i)})} \lambda^{2(k-j)}} + \rho\frac{\sum_{j\in J_k(u^{(i)})} \lambda^{(k-j)}\, \varepsilon_j}{\sum_{j\in J_k(u^{(i)})} \lambda^{2(k-j)}}$$

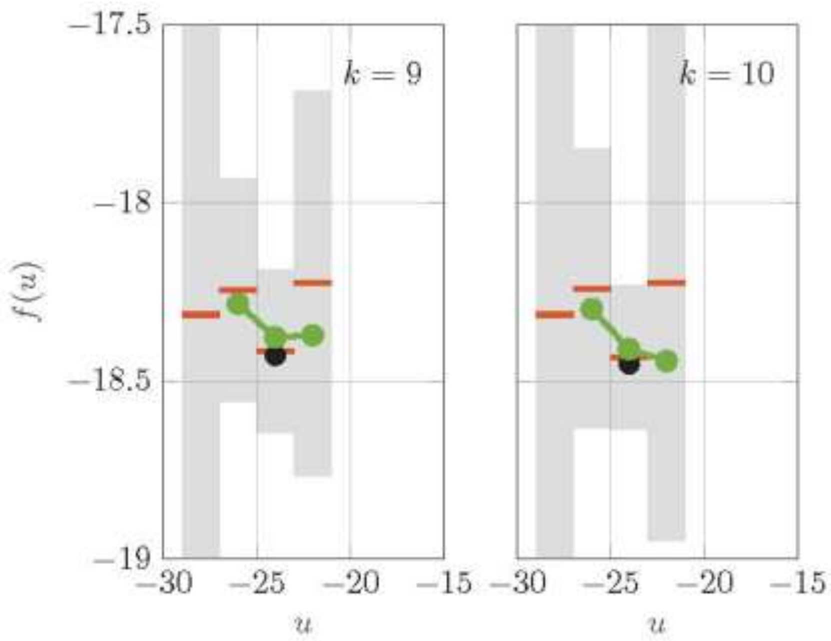
set of previous measurements

expected value

uncertainty

Uncertainty-based perturb and observe: decision

Build a local model around the current input



Three-point "flexible beam" model

- Piece-wise linear through expected values when uncertainties are low
- More linear for higher uncertainties

Pick the next input

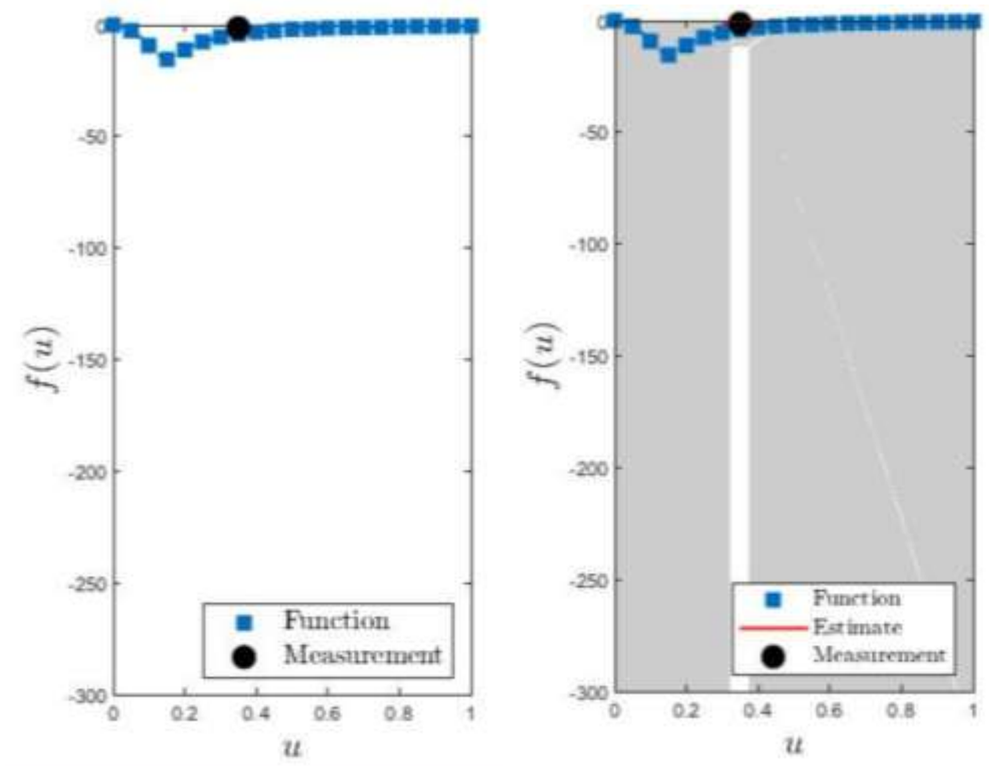
The lowest point of the "flexible beam" gives the highest expected improvement

Tuning parameters:

- "Flexibility" of beam
- Uncertainty development over time

Uncertainty-based perturb and observe: results

Comparison: P&O and uP&O



Main idea uP&O:

- Trial and error leads to estimate of optimum location
- Model measurement noise and increase uncertainty over time
- Exploration/exploitation trade-off: only perturb when uncertainty about current optimum is high
- Implementation: pick the lowest point as the next input

Result: fast tracking of time-varying optima, with limited unnecessary perturbations

How does uncertainty-based perturb and observe address the requirements?

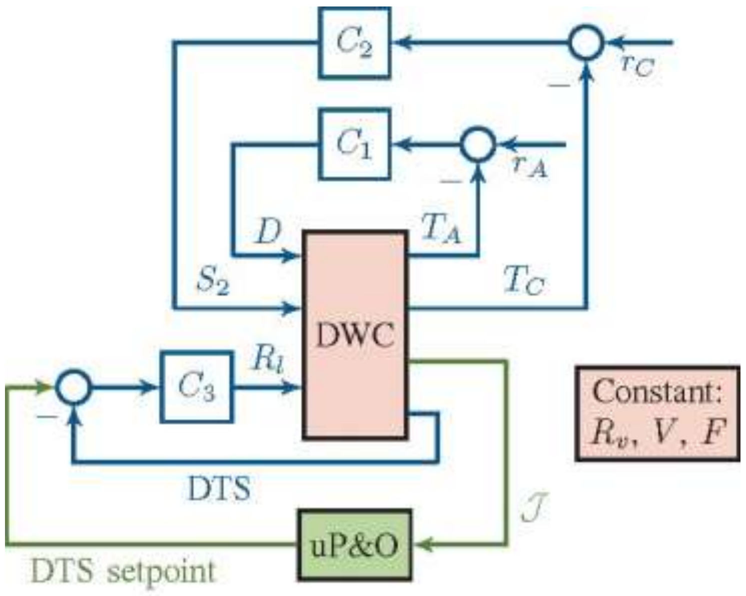
✓	Find and track a time-varying optimal operating point
✓	Use very limited model knowledge • Needs estimates of uncertainty and rate of time-variation
✓	Deal with data that gets less relevant over time • Model and monitor data reliability through uncertainty
✓ ✓	Easy implementation in ongoing process Limited disruption of ongoing process • Only requires small changes in input variable • Only perturb when uncertainty is high
	Demonstrate feasibility on a real system

Experiments on a dividing wall distillation column

- Dividing wall distillation column
  - Two thermally-coupled distillation columns that can separate up to four products
  - Up to 30% more efficient if operated at its optimum
  - Control setup: feedback for top and bottom product purity, perturbation-based optimization for side product
  - Location of the optimum is unknown

- Motivation for these experiments
  - Industrial ("complicated") setup with existing control strategy
  - Show that perturbation-based optimization can work for real systems
  - Demonstrate the functionality of our method

Optimal operation ➡ maximum side-stream purity

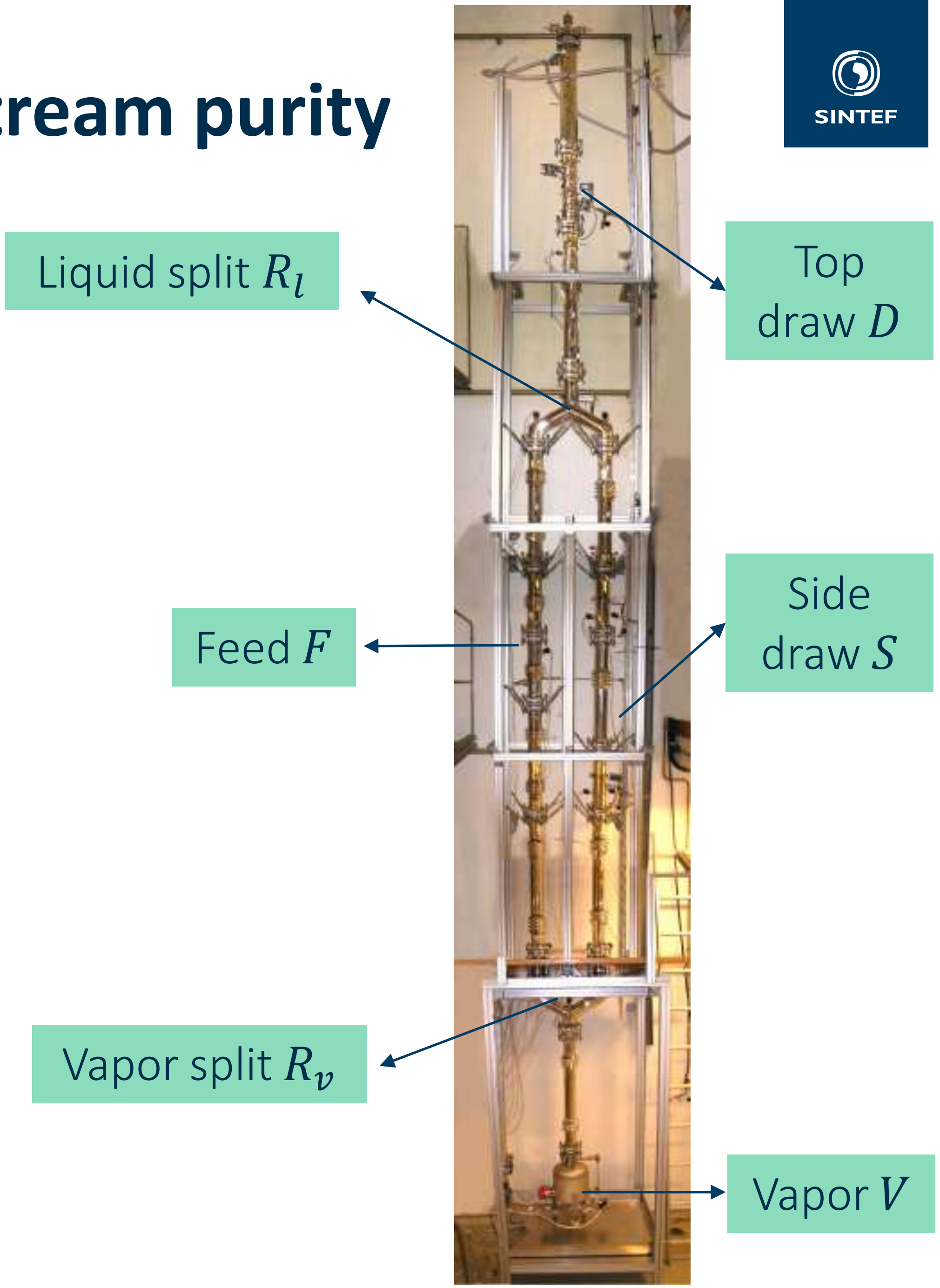


Measurable cost function with single optimum?

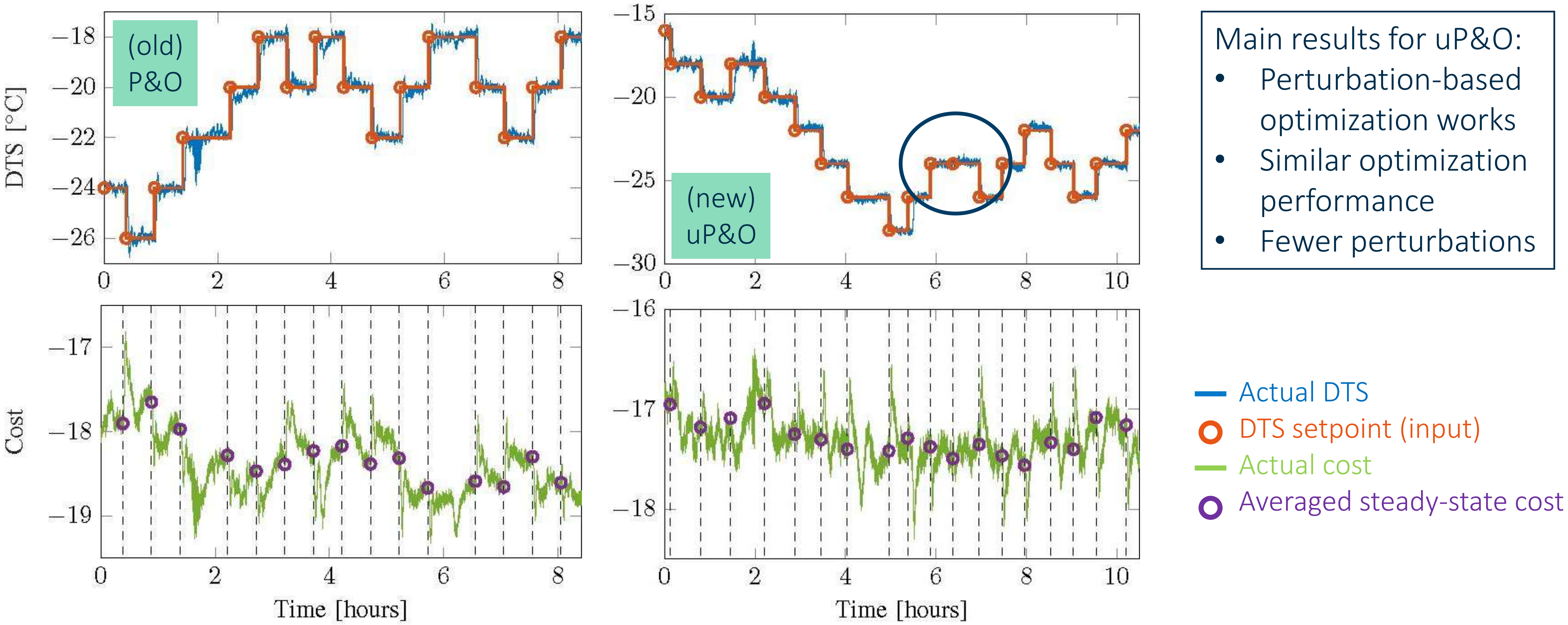
- Yes, through side-product purity or correlation with temperature profile

Safe input variable for optimization?

- Yes, liquid split, either directly or indirectly through feedback using "Difference Temperature Symmetry" (DTS)



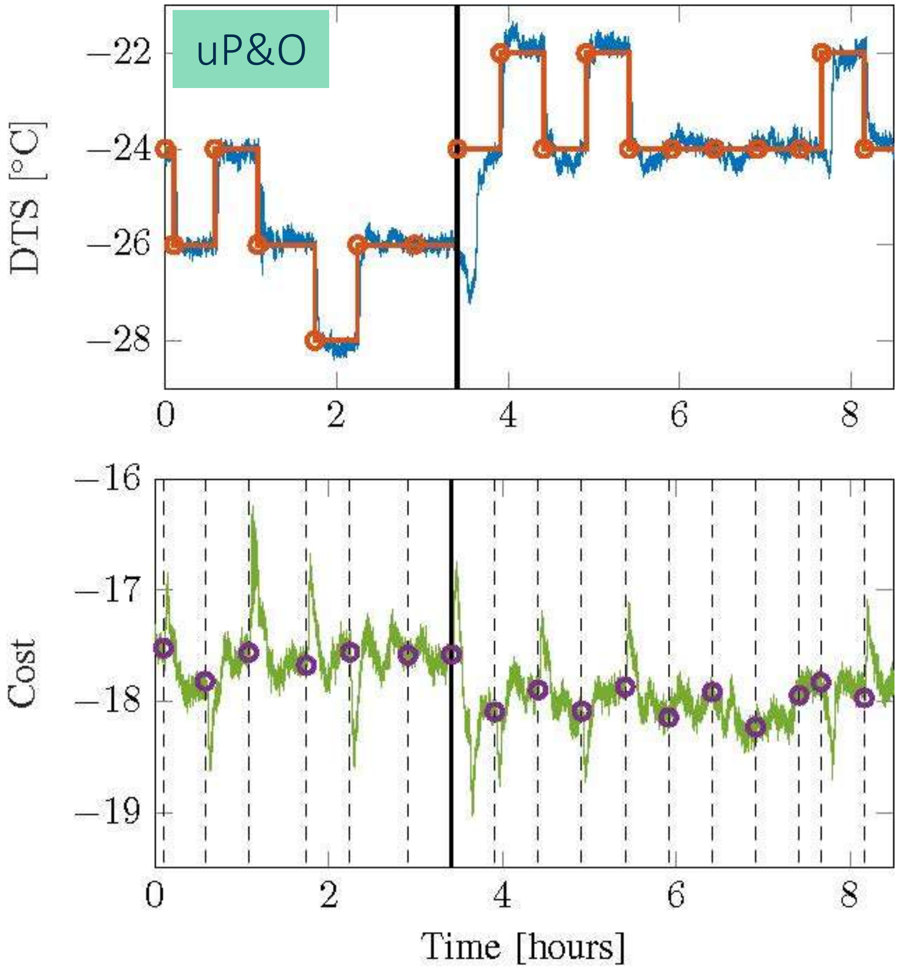
Experimental results (cost minimization)



Main results for uP&O:

- Perturbation-based optimization works
- Similar optimization performance
- Fewer perturbations

Experimental results: disturbances



Main result for uP&O with disturbances:

- Fast testing and re-optimization after optimum changes

Other take-aways for uP&O implementation

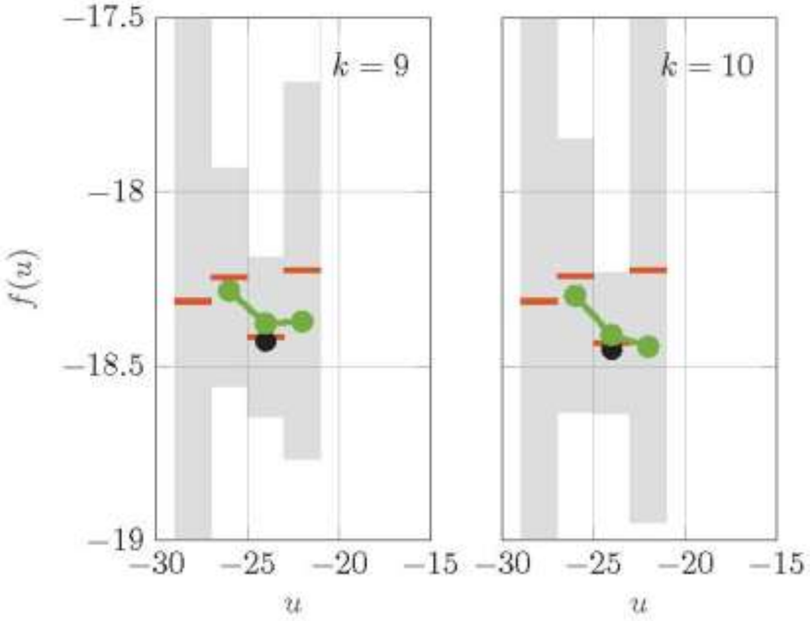
- Applicable to problems with single optimum
- Only requires a measurable cost function and a changeable input variable
- Takes small steps – less risky than global searches
- Based on estimates of measurement uncertainty and timescale of optimum changes

Expected result: more time spent at optimal input; decreased wear, resource usage and operational cost

Summary: optimization of uncertain processes

- Fast and safe optimum tracking through perturbation-based optimization
- Intuitive optimization layer to add to existing systems (also as decision support)
- Uncertainty-based approach limits unnecessary perturbations

- Want to know more?
  - L. Aarnoudse, M. Haring, N. van de Wouw, and A. Pavlov, ““Uncertainty-based perturb and observe for data-driven optimization,” ArXiv preprint 2604.15922.
  - I. J. Halvorsen et al., “Extremum seeking control by perturb and observe applied to dividing wall column pilot,” Systems and Control Transactions, 5:2433-2440, 2026.
  - Or contact me: mark.haring@sintef.no



Teknologi for et bedre samfunn