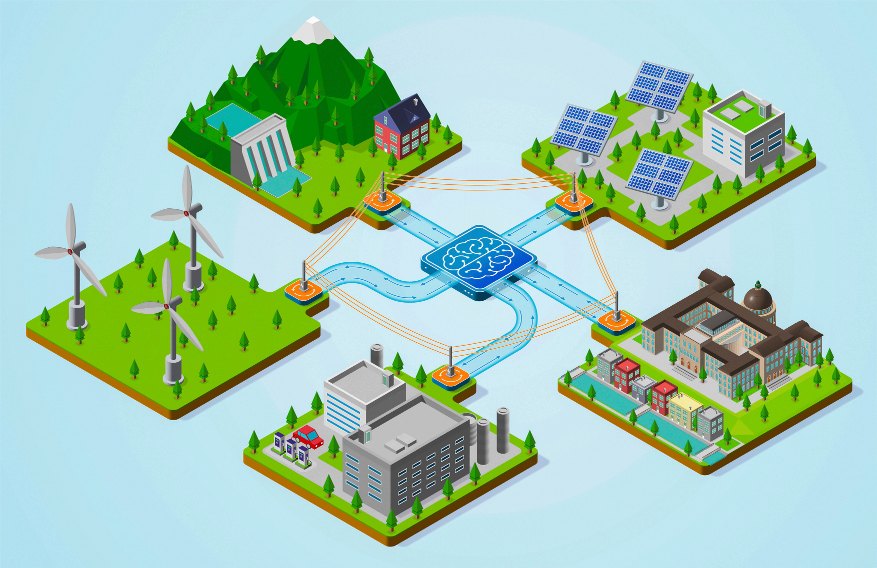
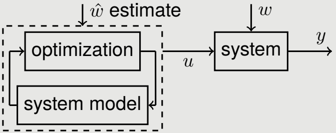


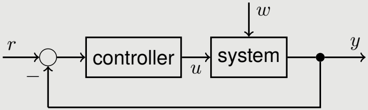
Online Feedback Optimization for Power Systems Operation

Florian Dörfler & Saverio Bolognani ETH Zürich

feedforward planning vs. feedback control

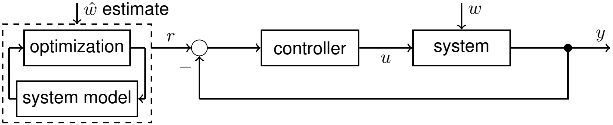


- **complex specifications & decision**
  optimal, constrained, & multivariable
- **strong requirements**
  precise model, full state, disturbance estimate, & computationally intensive



- **simple feedback policies**
  suboptimal, unconstrained, & SISO
- **forgiving nature of feedback**
  measurement driven, robust to model uncertainty, fast & agile response

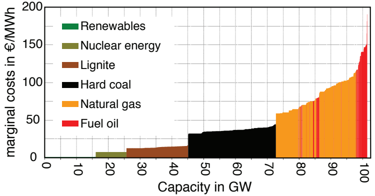
$\rightarrow$ typically **complementary** methods are combined via **time-scale separation**

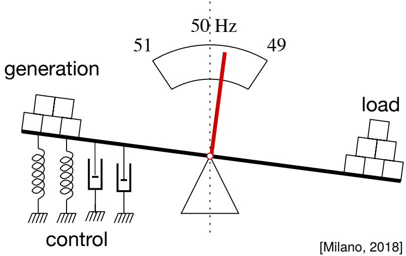


offline & feedforward | **real-time & feedback**

Price of time-scale separation in power balancing

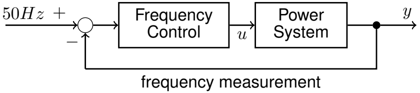
- **offline optimization**: dispatch based on forecasts of loads & renewables





[Milano, 2018]

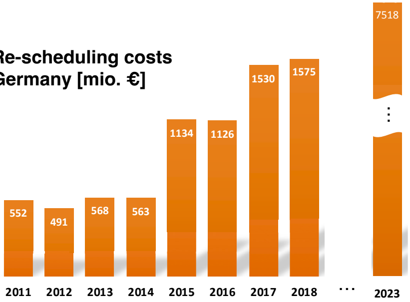
- **online control** based on frequency



- **re-schedule set-point** to mitigate severe forecasting errors (redispatch, reserve, etc.)

more uncertainty & fluctuations → **infeasible & inefficient** to separate optimization & control

Re-scheduling costs Germany [mio. €]

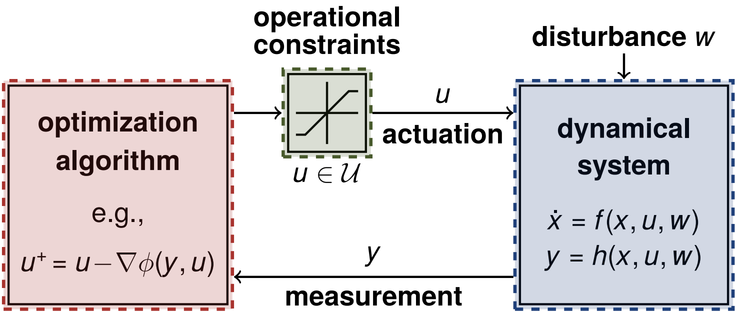


[Bundesnetzagentur, Monitoringbericht 2012-2019]

Synopsis & proposal for control architecture

- **power grid**: separate decision layers hit limits under increasing uncertainty
- similar observations in other **large-scale & uncertain control systems**: process control systems & queuing / routing / infrastructure networks

proposal: $\underbrace{\textbf{open}}_{\text{with inputs \& outputs}}$ and $\underbrace{\textbf{online}}_{\text{running \& non-batch}}$ **optimization algorithm** as $\underbrace{\textbf{feedback}}_{\text{real-time interconnected}}$ control



Context: historical roots & related work

- **process control**: reducing the effect of uncertainty in sucessive optimization
  Optimizing Control [Garcia & Morari, '81 & '84], *Self-Optimizing Control* [Skogestad, '00], *Modifier Adaptation* [Marchetti et. al, '09], *Real-Time Optimization* [Bonvin ed. '17, Krishnamoorthy et al. '22], ...

- optimal routing, queuing, & congestion control in **communication networks** (e.g. TCP/IP) [Kelly et al., '98], [Low, Paganini, & Doyle '02], [Srikant '12], ... & in **power systems** [Jokic et al '09], [Bolognani & Zampieri '13], [Dall'Anese & Simonetto '16], [Hauswirth et al, '16], ...

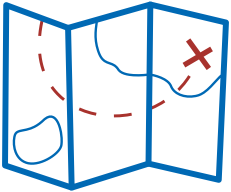
- **extremum-seeking**: derivative-free & suited for unconstrained low-dim. problems
  [Leblanc, 1922], ...[Wittenmark & Urquhart, 1995], ...[Krstić & Wang, 2000], ..., [Feiling et al., 2018]

- **real-time MPC** with *anytime* guarantees for dynamic (optimal control) problems:
  [Diel et al. 2005], [Zeilinger et al. 2009], [Feller & Ebenbauer 2017], ...[Liao-McPherson et al. '20]

- **policy gradient RL**: optimal control solved by model-free gradient interactions with plant: [Kadake '01], [Peters & Schaal, '07], [Duan et al. '16], [Fazel et al. '19], ...[Hu et al. '23]

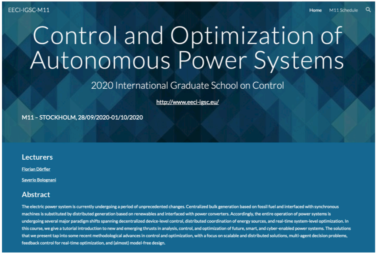
- recent **system theory** involving regulation, robust, hybrid control, etc.: [Lawrence et al. 2018], [Colombino et al. 2018], [Simpson-Porco '20], [Hauswirth et al, '20], [Bianchin, Poveda, '22], ...

Outline of today

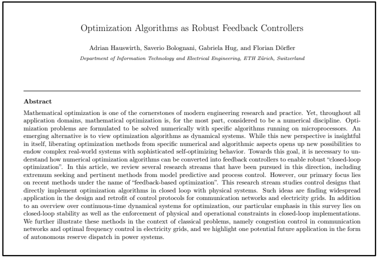


- **theory**: optimization algorithms in closed loop
  - **tutorial**: stylized example & academic analysis
  - **extensions:** practical, performant, & model-free
  - **game theory**: the real world ain't optimization
- **power systems** case studies: sims $\rightarrow$ industry deployment

Main resources for today



https://sites.google.com/view/eeci-autonomous-power-systems



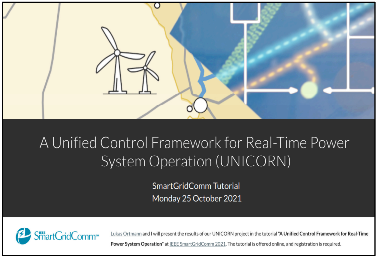
Optimization Algorithms as Robust Feedback Controllers

Adrian Hauswirth, Saverio Bolognani, Gabriela Hug, and Florian Dörfler
Department of Information Technology and Electrical Engineering, ETH Zürich, Switzerland

Abstract

Mathematical optimization is one of the cornerstones of modern engineering research and practice. Yet, throughout all application domains, mathematical optimization is, for the most part, considered to be a numerical discipline. Optimization problems are formulated to be solved numerically with specific algorithms running on microprocessors. An emerging alternative is to view optimization algorithms as dynamical systems. While this new perspective is insightful in itself, liberating optimization methods from specific numerical and algorithmic aspects opens up new possibilities to endow complex real-world systems with sophisticated self-optimizing behavior. Towards this goal, it is necessary to understand how numerical optimization algorithms can be converted into feedback controllers to enable robust "closed-loop optimization". In this article, we review several research streams that have been pursued in this direction, including extremum seeking and pertinent methods from model predictive and process control. However, our primary focus lies on recent methods under the name of "feedback-based optimization". This research stream studies control designs that directly implement optimization algorithms in closed loop with physical systems. Such ideas are finding widespread application in the design and retrofit of control protocols for communication networks and electricity grids. In addition to an overview over continuous-time dynamical systems for optimization, our particular emphasis in this survey lies on closed-loop stability as well as the enforcement of physical and operational constraints in closed-loop implementations. We further illustrate these methods in the context of classical problems, namely congestion control in communication networks and optimal frequency control in electricity grids, and we highlight one potential future application in the form of autonomous reserve dispatch in power systems.

2021 Survey paper https://arxiv.org/abs/2103.11329



2021 SmartGridComm Tutorial here

Publications about 'Online Optimization'

Articles in journal, book chapters

1. V. Häberle, A. Hauswirth, L. Ortmann, S. Bolognani, and F. Dörfler. **Non-convex Feedback Optimization with Input and Output Constraints**. *IEEE Control Systems Letters*, 5(1):343-348, 2021. Keyword(s): Online Optimization, Nonlinear Optimization, Nonlinear Control Design. [bibtex-entry]
2. A. Hauswirth, S. Bolognani, and F. Dörfler. **Projected Dynamical Systems on Irregular Non-Euclidean Domains for Nonlinear Optimization**. *SIAM Journal on Control and Optimization*, 59(1):635-668, 2021. Keyword(s): Online Optimization, Nonlinear Optimization. [bibtex-entry]
3. A. Hauswirth, S. Bolognani, G Hug, and F. Dörfler. **Optimization Algorithms as Robust Feedback Controllers**. January 2021. Note: Submitted. Available at http://arxiv.org/abs/2103.11329. Keyword(s): Power Networks, Power Flow Optimization, Online Optimization, Nonlinear Optimization. [bibtex-entry]

Publications http://people.ee.ethz.ch/~floriand/

STYLIZED EXAMPLE & ACADEMIC ANALYSIS

Algorithm in closed loop with LTI dynamics

optimization problem

$$\begin{aligned} \underset{y,u}{\text{minimize}} \quad & \phi(y,u) \\ \text{subject to} \quad & y = H_{io} u + H_{do} w \\ & u \in \mathcal{U} \end{aligned}$$

$\rightarrow$ scaled & open projected gradient flow

$$\dot{u} = \Pi_{\mathcal{U}}\Big(-\epsilon \big[H_{io}^T \ \ \mathbb{I}\big] \cdot \nabla \phi(\boldsymbol{y}, u)\Big)$$

requiring only steady-state sensitivity H_{io}

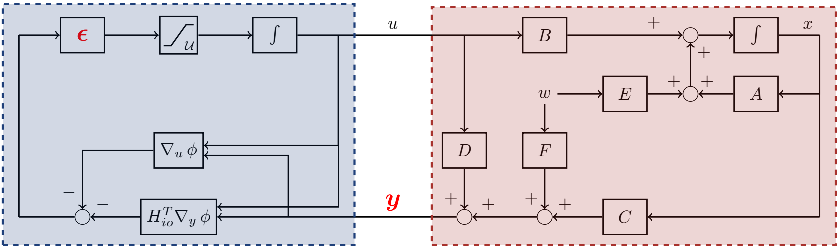
LTI dynamics

$$\begin{aligned} \dot{x} &= Ax + Bu + Ew \\ y &= Cx + Du + Fw \end{aligned}$$

const. disturbance w & steady-state maps

$$x = \underbrace{-A^{-1}B}_{H_{is}} u \ \underbrace{-A^{-1}E}_{H_{ds}} w$$

$$y = \underbrace{(D - CA^{-1}B)}_{H_{io}} u + \underbrace{(F - CA^{-1}E)}_{H_{do}} w$$



Stability, feasibility, & asymptotic optimality

Theorem [Hauswirth et al. '20]: Assume that

- **regularity** of cost function ϕ: compact sublevel sets & ℓ-Lipschitz gradient
- LTI system **exp. stable** with rate $\tau > 0$: $\exists\, P \succ 0$ s.t. $PA + A^T P \preceq -2\tau P$
- sufficient **time-scale separation** (small gain): $0 < \epsilon < \epsilon^\star \triangleq \frac{2\tau}{\text{cond}(P)} \cdot \frac{1}{\ell\, \|H_{io}\|}$

$$\iff \boxed{\textit{system gain} \cdot \textit{algorithm gain} < 1}$$

Then the closed-loop system is **stable** & **globally converges** to the critical points of the **optimization problem** while remaining **feasible** at all times.

Proof: **LaSalle/Lyapunov** analysis via **singular perturbation** [Saberi & Khalil '84]

$$V_\delta(u,e) = \delta \cdot \underbrace{e^T P e}_{\text{LTI Lyapunov function}} + (1-\delta) \cdot \underbrace{\phi\big(y(u),u\big)}_{\text{algorithm merit function}}$$

with **parameter** $\delta \in (0,1)$ & steady-state **error coordinate** $e = x - H_{is}u - H_{ds}w$

$\to$ derivative $\dot{V}_\delta(u,e)$ is non-increasing if $\epsilon \leq \epsilon^\star$ & for judicious choice of δ

Highlights of online feedback optimization

Weak assumptions on plant

- internal stability

$\rightarrow$ no further structure required

- measurements & steady-state sensitivity

$\rightarrow$ no need for model, state, or disturbances

Weak assumptions on optimization

- Lipschitz gradient + properness

$\rightarrow$ no (strict / strong) convexity required

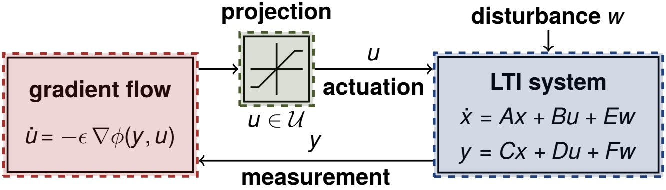
Parsimonious but powerful setup

- weak assumptions: sensitivity + time-scale separation (liftable [Bianchi @CDC])
- strong conclusions: stability, feasibility (safety), & convergence to optimality
- **robust & extendable methodology**

$\rightarrow$ nonlinear & sampled-data dynamics

$\rightarrow$ general equilibrium seeking algorithms

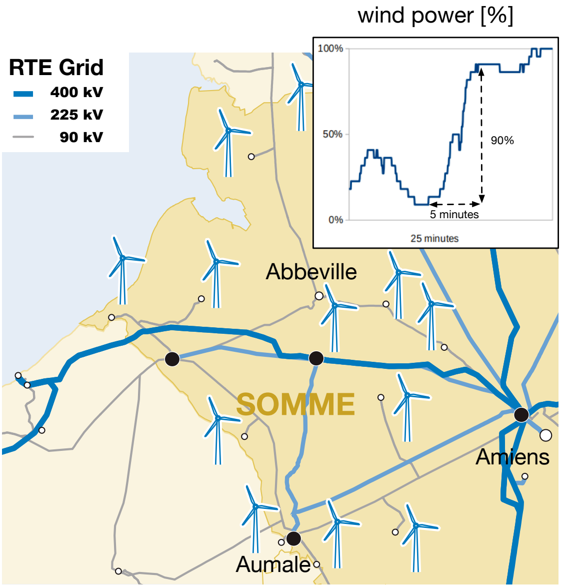
$\rightarrow$ disturbances, noise, model-free, . . .



$\boxed{\textbf{take-away:}}$ open online optimization algorithms can be applied in feedback & methodology is robust + extendable

TRUST ME THAT EVERYTHING EXTENDS $\longrightarrow$ EXAMPLES

One use-case: power grid operation



UNICORN project with RTE

- automation of *Blocaux* zone
- **rapid change** in generation

  → **line / voltage limits** violations

  → resolve most **economically** & under severe **uncertainty** & time-varying **disturbances**

Technical problem setup

- actuation & sensing in Blocaux

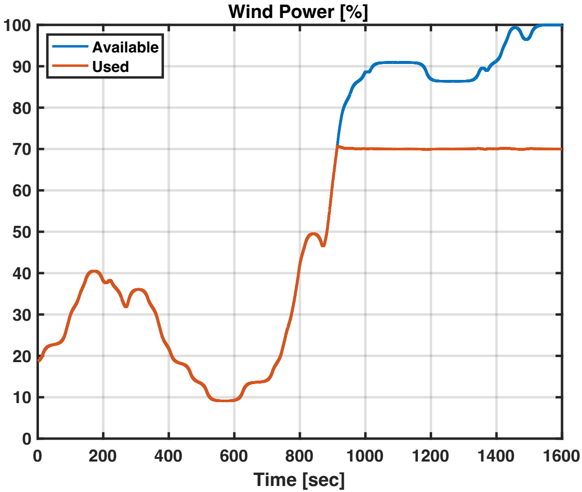
  → tap, reactive & active power

  → voltage & current magnitudes
- simulation of entire French grid

  → power flow + tap changer
- realistic constraints & cost

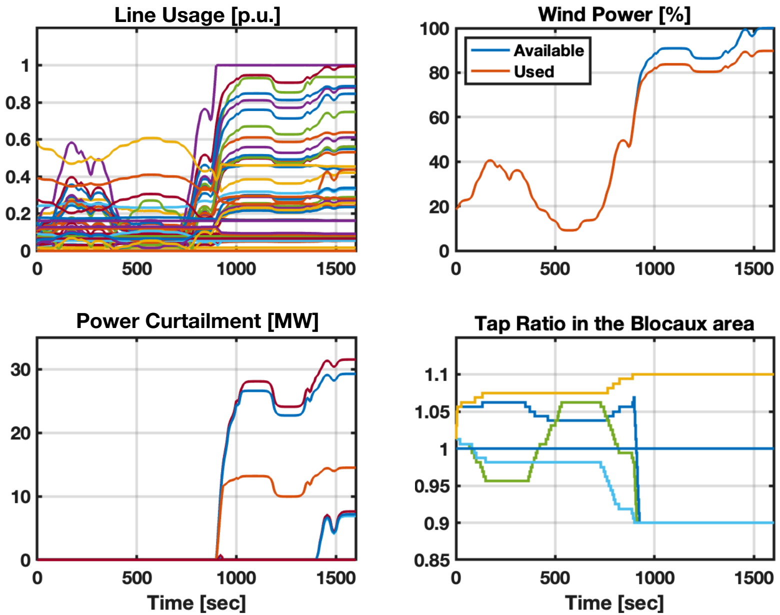
  → curtailment + losses

Standard mode of operation



offline optimization & **curtailment at 70%** to not violate line / voltage limits

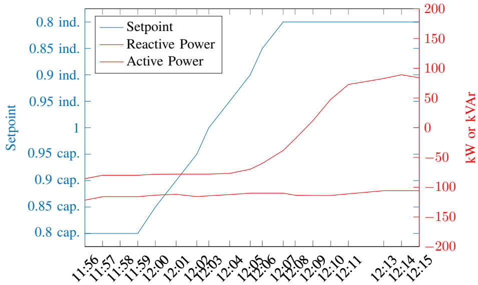
Feedback optimization using **wrong model** sensitivity



IN VIVO

Commercial deployment at Swiss DSO

- **virtual grid reinforcement** through reactive power/voltage support
- **strong economic incentives** (rewards & penalties) from higher-level system operator
- **feedback optimization** on legacy hardware
- **runs robustly 24 / 7 & makes money** in presence of time-varying incentives

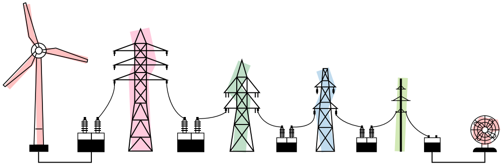


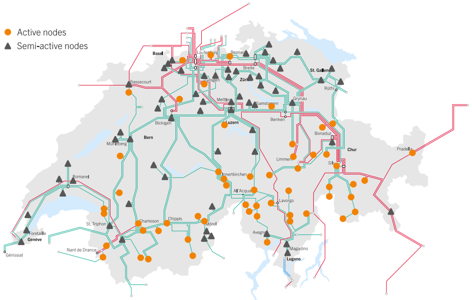
→ Ortmann et al. (2022) **"Deployment of an Online ..."**

THE WORLD IS NOT AN OPTIMIZATION PROBLEM

$\longrightarrow$ **GAME-THEORETIC PERSPECTIVE**

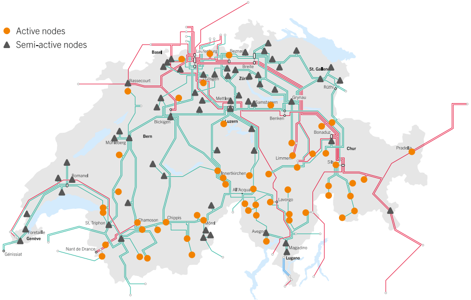
TSO-DSO coordination

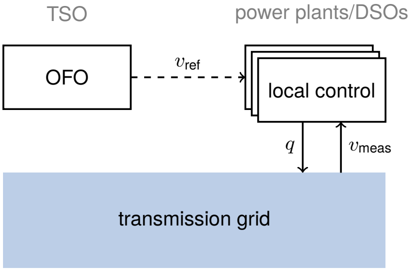




- **Power plants with exhausted resources** – hydro storage power plants with empty reservoirs
- **TSOs increasing reactive power needs** – transmission grid expansion
- **Energy transition and decentralization** – decentralized feed-in of electricity
- **Congested tie lines** – minimize the exchange of reactive energy with other countries to make the lines available for active power

Voltage support procurement from DSOs





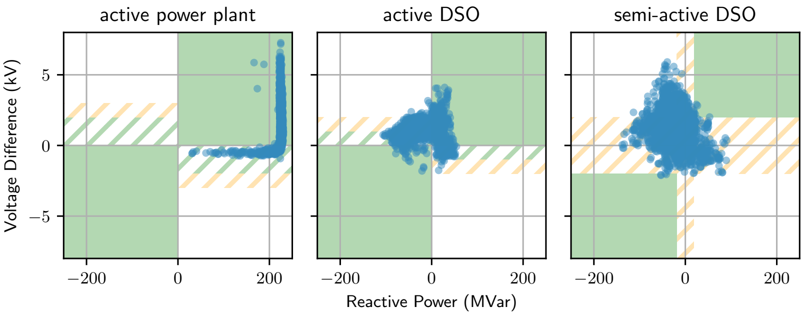
- DSOs as **tracking controllers**
  - receive a reference signal v_{ref}
  - measure local voltage v_{meas}
  - aim at tracking by controlling their reactive power demands q
- **Financial incentives** have been designed *ex-post*

Incentives and empirical data

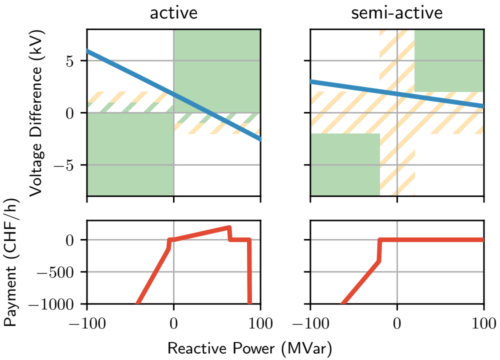
Swissgrid reactive power incentive

- proportional to $|q|$
- positive payment (reward) if "conform"
- negative payment (penalty) if "non-conform"

$$\mathcal{P}(q_i, v_i, u) \approx u q_i \operatorname{sign}(v_i - v_{\text{ref},i})$$



The DSO "best response" problem



DSO do not simply **track a reference** but, instead, try to solve

$$
\begin{aligned}
q_{\text{opt},i} = \arg\min_{\xi_i} \quad & c_i(\xi_i) - \mathcal{P}(\xi_i, v_i(\xi_i, q_{-i}, d), u) \\
\text{subject to} \quad & q_{\text{min},i} \leq \xi_i \leq q_{\text{max},i} \\
& v_{\text{min},i} \leq v_i(\xi_i, q_{-i}, d) \leq v_{\text{max},i}
\end{aligned}
$$

$q_{\text{opt},i}$ optimal reactive power demand of DSO i

v_i voltage at substation i

q_{-i} reactive power demand of other DSOs

d unknown state of the grid

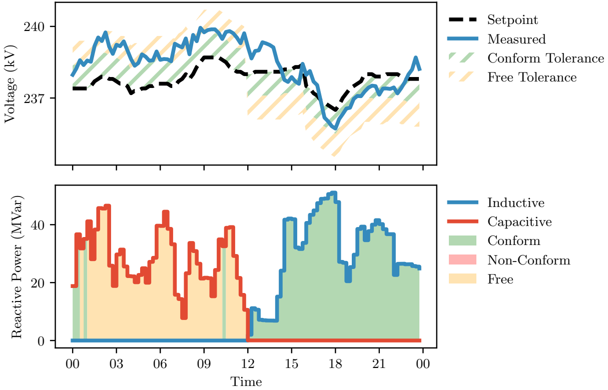
u incentive parameters of payment $\mathcal{P}$

c cost of reactive power

Poor voltage reference tracking

- High reactive power cost?
- Limited reactive power resources?
- Multiple equilibria?
- Collusion?

All observed in data!



Best-response as part of the plant model

Incentives should not be designed *ex post*, but used as a **real-time control signal**.

Stackelberg game / bilevel optimization

$$
\begin{aligned}
\min_{u} \quad & f(u) + g(y) \\
\text{subject to} \quad & u_{\text{min}} \leq u \leq u_{\text{max}} \\
& c_j(y) \leq 0 \quad j = 1, \ldots, J \\
& y = h(u, w)
\end{aligned}
$$

- u contains **incentive parameters**
- $h(u, w)$ models the input/output algebraic map, i.e., both
  - **power flow equations**
  - **strategic response of the DSOs**

Example: procurement of volt/VAr regulation

$$\begin{aligned} \min_{v,q,u} \quad & g(v(q,d)) \qquad \text{e.g., } \|v - v_{\text{ref}}\|^2 \\ \text{subject to} \quad & \boxed{\begin{aligned} \forall i: \quad q_i = \; & \arg\min_{\xi_i} \quad c_i(\xi_i) - \mathcal{P}(\xi_i, v_i(q,d), u_i) \\ & \text{subject to} \quad q_{\min,i} \leq \xi_i \leq q_{\max,i} \end{aligned}} \end{aligned}$$

DSOs' best response

Incentive update via Online Feedback Optimization

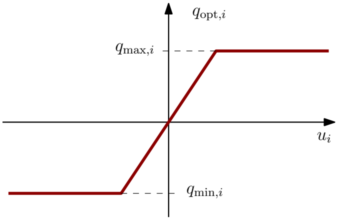
Online optimization can be employed as before (projected gradient, primal-dual flows, ...).

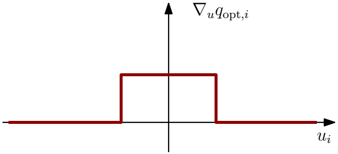
Driven by **gradient**

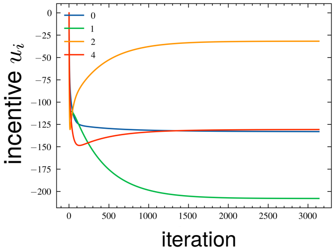
$$\underbrace{\nabla_u q_{\text{opt}}(v,d,u)^\top}_{\text{best-response sensitivities}} \cdot \underbrace{\nabla_q v(q,d)^\top}_{\text{power flow sensitivities}} \cdot \underbrace{\nabla_v g(v)}_{\text{cost gradient}}$$

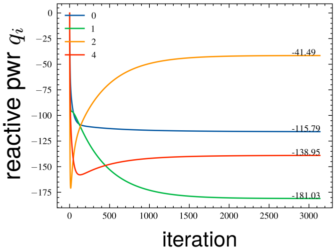
Numerical example

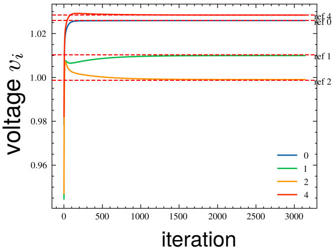
Quadratic reactive power cost c_i
+ linear constraints
$\rightarrow$ **piecewise affine best response**



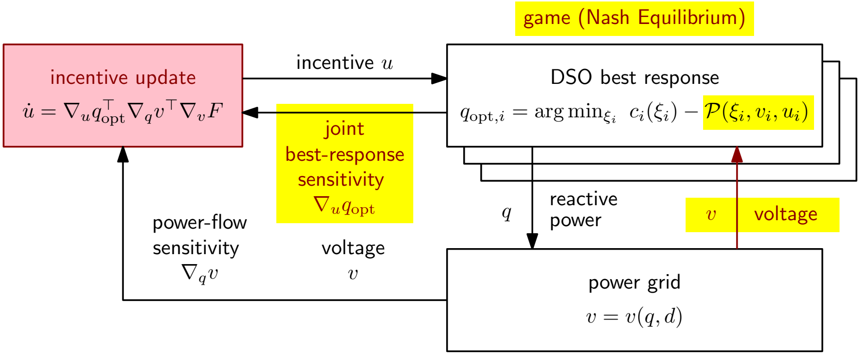








Co-design of real-time operations and incentives



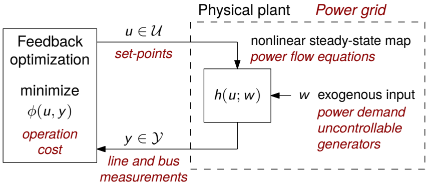
The sensitivity of **best-response maps** can be computed iteratively

P. D. Grontas, G. Belgioioso, C. Cenedese, M. Fochesato, J. Lygeros, F. Dörfler

BIG Hype: Best Intervention in Games via Distributed Hypergradient Descent

IEEE Transactions on Automatic Control, 2024

Conclusions



Real-time grid operations via OFO

- Parallel automation of multiple remedial actions
- Robustness to model uncertainty
- Online optimization driven by grid measurements

Procurement of control services from DSOs

- Game-theoretic multi-follower problem
- Best-response part of the "physics"
- Seamlessly integrated in OFO