Online Feedback Optimization

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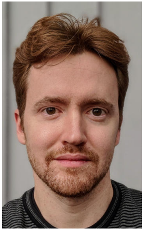
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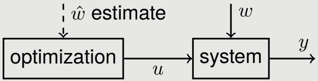
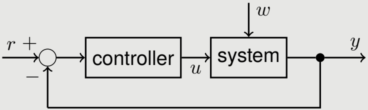
feedforward optimization vs. feedback control

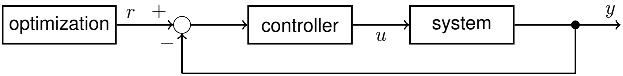


- **complex specifications & decision**
  optimal, constrained, & multivariable
- **strong requirements**
  precise model, full state, disturbance estimate, & computationally intensive



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

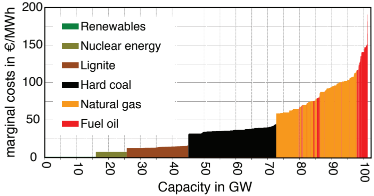
$\rightarrow$ typically **complementary** methods are combined via **time-scale separation**

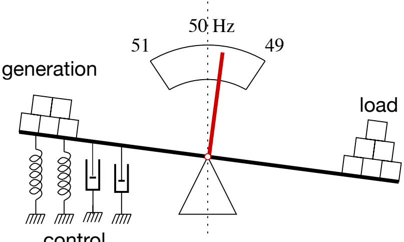


offline & feedforward | **real-time & feedback**

Example: power system balancing

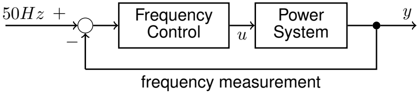
- **offline optimization**: dispatch based on forecasts of loads & renewables





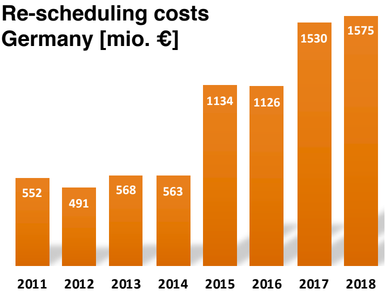
[Milano, 2018]

- **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

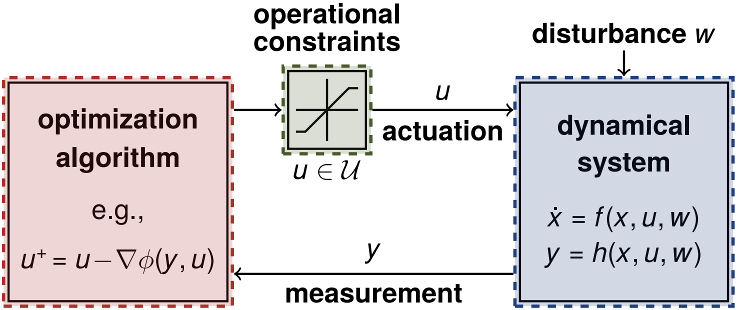


[Bundesnetzagentur, Monitoringbericht 2012-2019]

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: **open** (with inputs & outputs) and **online optimization algorithm** (running & non-batch) as **feedback** (real-time interconnected) control



Historical roots & conceptually related work

- **process control**: reducing the effect of uncertainty in sucessive optimization *Optimizing Control* [Garcia & Morari, 1981/84], *Self-Optimizing Control* [Skogestad, 2000], *Modifier Adaptation* [Marchetti et. al, 2009], *Real-Time Optimization* [Bonvin, ed., 2017], . . .

- **extremum-seeking**: derivative-free but hard for high dimensions & constraints [Leblanc, 1922], . . . [Wittenmark & Urquhart, 1995], . . . [Krstić & Wang, 2000], . . . , [Feiling et al., 2018]

- **MPC** with *anytime* guarantees (though for dynamic optimization): real-time MPC [Zeilinger et al. 2009], real-time iteration [Diel et al. 2005], [Feller & Ebenbauer 2017], etc.

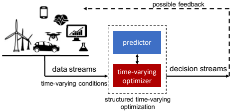
- optimal routing, queuing, & congestion control in **communication networks**: e.g., TCP/IP [Kelly et al., 1998/2001], [Low, Paganini, & Doyle 2002], [Srikant 2012], [Low 2017], . . .

- **optimization algorithms as dynamic systems**: much early work [Arrow et al., 1958], [Brockett, 1991], [Bloch et al., 1992], [Helmke & Moore, 1994], . . . & recent revival [Holding & Lestas, 2014], [Cherukuri et al., 2017], [Lessard et al., 2016], [Wilson et al., 2016], [Wibisono et al, 2016], . . .

- recent **system theory** approaches inspired by output regulation [Lawrence et al. 2018] & robust control methods [Nelson et al. 2017], [Colombino et al. 2018], [Simpson-Porco 2020], . . .

Feedback optimization literature

- lots of recent theory development stimulated by **power systems** problems



A Survey of Distributed Optimization and Control Algorithms for Electric Power Systems

Daniel K. Molzahn,* Member, IEEE, Florian Dörfler,† Member, IEEE, Henrik Sandberg,‡ Member, IEEE, Steven H. Low,§ Fellow, IEEE, Sambuddha Chakrabarti,¶ Student Member, IEEE, Ross Baldick,¶ Fellow, IEEE, and Javad Lavaei,** Member, IEEE

Time-Varying Convex Optimization: Time-Structured Algorithms and Applications

Andrea Simonetto, Emiliano Dall'Anese, Santiago Paternain, Geert Leus, and Georgios B. Giannakis

Optimization Algorithms as Robust Feedback Controllers

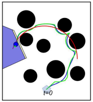
Adrian Hauswirth, Saverio Bolognani, Gabriela Hug, and Florian Dörfler
Department of Information Technology and Electrical Engineering, ETH Zürich, Switzerland

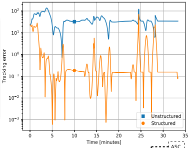
- **theory ↔ power literature**: KKT control [Jokic et al, 2009]
  → really kick-started ∼ 2013 by EU & US groups

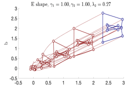
- **implemented** in microgrids (DTU, EPFL, Aachen . . .), demo projects (PNNL, NREL), & commercially (AEW)

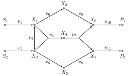
- feedback optimization increasingly **adopted** in robotics & process control domain + parallel work in comms

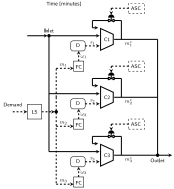
- **recent theory**: distributed, games, nonlinear, data, . . .



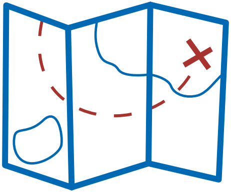








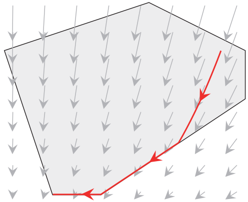
Overview



- **theory** : optimization algorithms in closed loop
  - stylized warm-up example & academic analysis
  - practical, robust, & performant extensions
- **power systems** case studies
  - device-level control & system-level operation
  - numerics, experiments, & industrial deployments

ACADEMIC WARM-UP PROBLEM: STYLIZED ALGORITHM DESIGN & CLOSED-LOOP ANALYSIS

Stylized optimization problem & algorithm



simple **optimization problem**

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

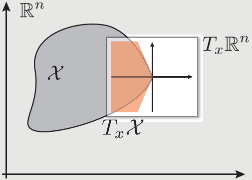
cont.-time **projected gradient flow**

$$\begin{aligned} \dot{u} &= \Pi^g_{\mathcal{U}}\Big(-\nabla\phi\big(h(u),u\big)\Big) \\ &= \Pi^g_{\mathcal{U}}\left(-\left[\tfrac{\partial h}{\partial u} \;\; \mathbb{I}\right] \cdot \nabla\phi(y,u)\right)\Big|_{y=h(u)} \end{aligned}$$

Fact: a regular† solution $u : [0,\infty] \to \mathcal{U}$ **converges** to critical points if ϕ has Lipschitz gradient & compact sublevel sets.

projected dynamical system

$$\dot{x} \in \Pi^g_{\mathcal{X}}[f](x) \triangleq \underset{v \in T_x\mathcal{X}}{\arg\min} \|v - f(x)\|_{g(x)}$$



- domain $\mathcal{X}$
- vector field f
- metric g
- tangent cone $T_x\mathcal{X}$

all sufficiently regular†

† for details → Hauswirth et al. (2021) **"Projected Dynamical Systems on Irregular Non-Euclidean Domains for Nonlinear Optimization"**

Algorithm in closed loop with LTI dynamics

optimization problem

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

$\rightarrow$ open & scaled projected gradient flow

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

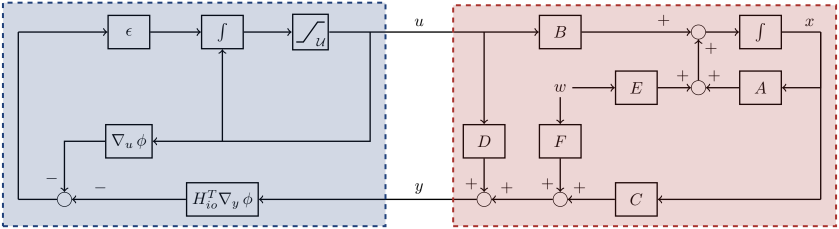
LTI dynamics

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

const. disturbance w & steady-state maps

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

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



Stability, feasibility, & asymptotic optimality

Theorem: Assume that

- **regularity** of cost function ϕ: compact sublevel sets & ℓ-Lipschitz gradient
- LTI system asymptotically **stable**: $\exists\, \tau > 0\,,\, \exists\, P \succ 0 :\; PA + A^T P \preceq -2\tau P$
- 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** and **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]

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

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

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

Example: optimal frequency control

- **dynamic LTI power system model**
  - economic balancing **objective**
  - **control** generation set-points
  - unmeasured load **disturbances**
  - **measurements**: frequency + constraint variables (injections & flows)

- ▶ linearized swing dynamics
- ▶ 1st-order turbine-governor
- ▶ primary frequency droop
- ▶ DC power flow approximation

- **optimization problem**

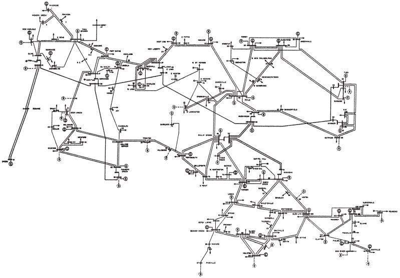
→ **objective**: $\phi(y,u) = \underbrace{\text{cost}(u)}_{\text{economic generation}} + \underbrace{\tfrac{1}{2}\|\max\{0, \underline{y} - y\}\|_{\Xi}^2 + \tfrac{1}{2}\|\max\{0, y - \overline{y}\}\|_{\Xi}^2}_{\text{operational limits (line flows, frequency, ...)}}$

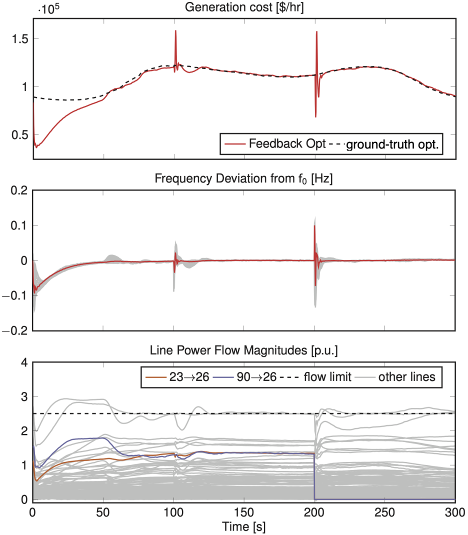
→ hard **constraints**: $\underbrace{\text{actuation } u \in \mathcal{U}}_{\text{enforced by projection}}$ & $\underbrace{\text{steady-state map } y = H_{io}u + R_{do}w}_{\text{enforced by physics}}$

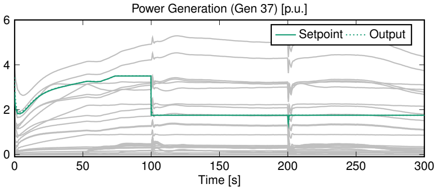
→ **control** $\dot{u} = \Pi_{\mathcal{U}}(\ldots \nabla\phi) \equiv$ super-charged Automatic Generation Control

Test case: contingencies in IEEE 118 system

events: generator outage at 100 s & double line tripping at 200 s

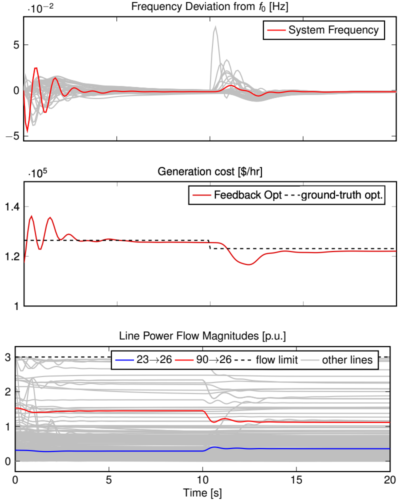




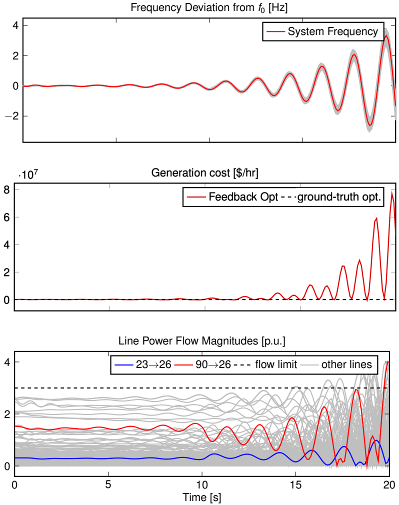


How conservative is $\epsilon < \epsilon^\star$?

still **stable for** $\epsilon = 2\,\epsilon^\star$



unstable for $\epsilon = 10\,\epsilon^\star$



Note: conservativeness depends on the problem, e.g., on soft penalty scalings

Highlights & comparison of our approach

Weak assumptions on plant

- internal stability

→ no observability / controllability

→ no passivity or primal-dual structure

- measurements & steady-state sensitivity

→ no knowledge of model or disturbances

→ no full state measurement

→ steady-state constraint enforced by plant

Weak assumptions on cost

- Lipschitz gradient + properness

→ no (strict / strong) convexity required

⟶ **all of these insights** extend to much more general problem setups !

Parsimonious but powerful setup

- potentially conservative bound on time-scale separation — but

→ **minimal assumptions** on control system & optimization problem

- **robust & extendable methodology**

→ nonlinear & sampled-data dynamics

→ general equilibrium seeking algorithms

→ time-varying disturbances, noise, . . .

take-away: open online optimization algorithms can be applied in feedback

→ Hauswirth et al. (2020)
"Timescale Separation in Autonomous Optimization"

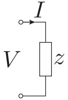
→ Menta et al. (2018)
"Stability of Dynamic Feedback Optimization . . ."

GENERAL NONLINEAR SYSTEMS & DISTURBANCES

Motivation: steady-state AC power flow

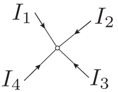
- **stationary model**

Ohm's Law



$V = zI$

Current Law



$0 = I_1 + \ldots + I_k$

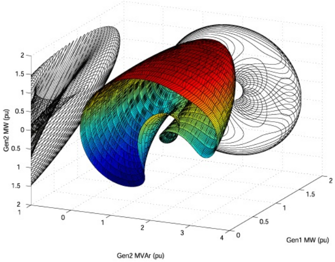
AC power $S = VI^*$

AC power flow equations

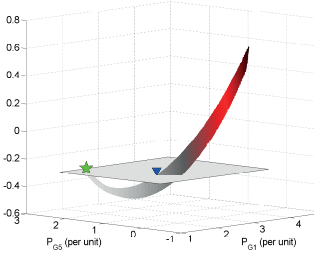
$$S_k = \sum_{l \in N(k)} \frac{1}{z^*_{kl}} V_k (V^*_k - V^*_l) \quad \forall k \in \mathcal{N}$$

- imagine **constraints slicing** this set
  $\Rightarrow$ nonlinear, non-convex, disconnected
- additionally the parameters are $\pm 20\%$ **uncertain** . . . this is only the steady state!

- **graphical illustration** of AC power flow

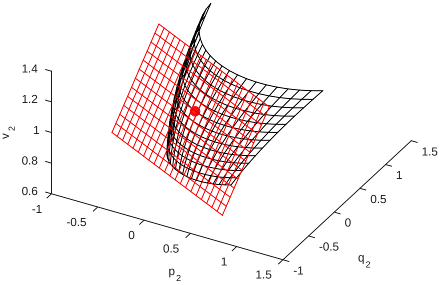


[Hiskens, 2001]



[Molzahn, 2016]

Key insights on physical equality constraint



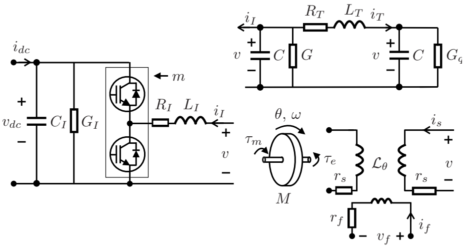
- AC power flow is complex but takes the form of a **smooth manifold**

→ local tangent plane approximations, local invertibility, & generic LICQ

→ **regularity** (algorithmic flexibility)

→ Bolognani et al. (2015)
"Fast power system analysis via implicit linearization of the power flow manifold"

→ Hauswirth et al. (2018)
"Generic Existence of Unique Lagrange Multipliers in AC Optimal Power Flow"



- AC power flow is **attractive steady state** for ambient physical dynamics

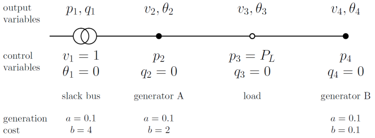
→ physics enforce feasibility even for non-exact (e.g., discrete) updates

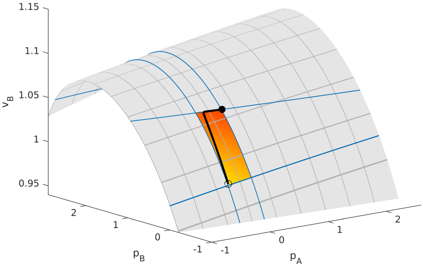
→ **robustness** (algorithm & model)

→ Gross et al. (2018)
"On the steady-state behavior of a nonlinear power system model"

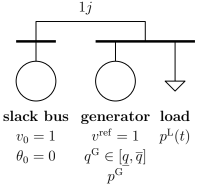
Simple low-dimensional case studies . . .

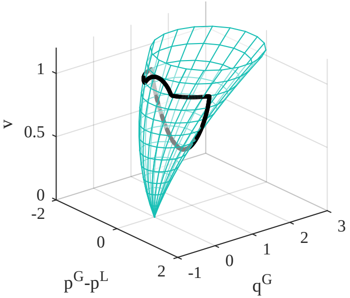
. . . can have **simple** feasible sets





. . . or can have **really complex** sets





application demands **sophisticated level of generality**!

General nonlinear systems & disturbances

- Lipschitz continuous **nonlinear system** $\dot{x} = f(x,u)$ (output setup also possible)
- explicit & differentiable **steady-state map** $x = h(u)$ so that $f(h(u),u) = 0$
- open-loop stable: **Lyapunov function** $W(x,u) \approx W(x - h(u))$ w.r.t **steady-state error**

satisfying $\underbrace{\dot{W}(x,u) \leq -\gamma \, \|x - h(u)\|^2}_{\text{dissipation rate } \gamma}$, $\underbrace{\|\nabla_u W(x,u)\| \leq \zeta \, \|x - h(u)\|}_{\zeta\text{-Lipschitz in steady-state error}}$

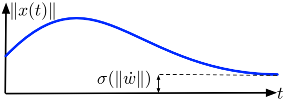
$\Rightarrow$ local / global closed-loop **stability, convergence to critical points, & feasibility** if

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

where the system gain is ζ/γ = Lipschitz constant / dissipation rate

- **time-varying disturbances**: $\dot{x} = f(x,u,w(t))$
- assume $\|\dot{w}(t)\|$ **bounded** & system is **input-to-state stable** (ISS) w.r.t. $\dot{w}$: $\dot{W} \leq -\gamma \, \|x - h(u,w)\|^2 + \sigma(\|\dot{w}\|)$

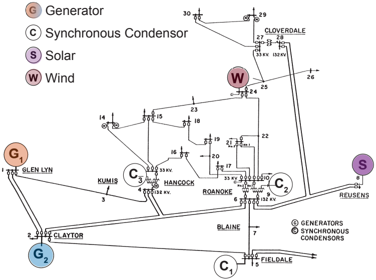
$\Rightarrow$ **tracking certificate:** closed-loop ISS w.r.t. $\dot{w}(t)$

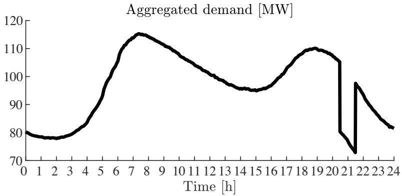


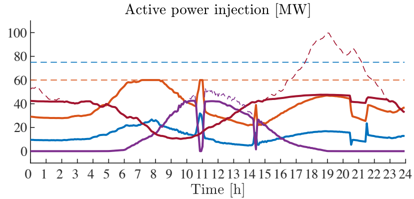
$\rightarrow$ Hauswirth et al. (2020) **"Timescale Separation in Autonomous Optimization"**

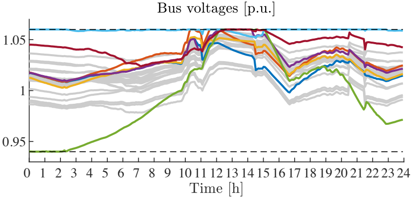
$\rightarrow$ Belgioioso et al. (2022) **"Online Feedback Equilibrium Seeking"**

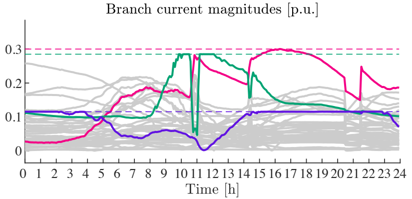
Tracking performance under disturbances







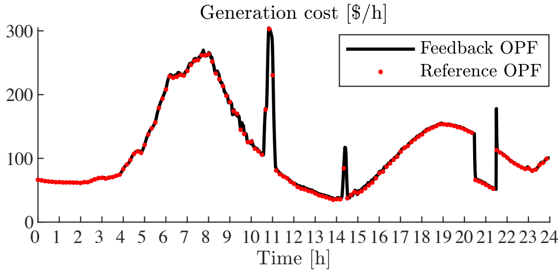




disturbance = net demand: load - (wind + solar)

Optimality despite disturbances & uncertainty

- transient trajectory **feasibility**
- practically **exact tracking** of ideal optimal power flow (OPF)
  (omniscient & no computation delay)
- **robustness** to model mismatch
  (asymptotic optimality under wrong model)



model uncertainty	offline optimization: feasible ?	offline optimization: $\phi - \phi^*$	offline optimization: $\|v - v^*\|$	feedback optimization: feasible ?	feedback optimization: $\phi - \phi^*$	feedback optimization: $\|v - v^*\|$
loads $\pm 40\%$	no	94.6	0.03	yes	0.0	0.0
line params $\pm 20\%$	yes	0.19	0.01	yes	0.01	0.003
2 line failures	no	-0.12	0.06	yes	0.19	0.007

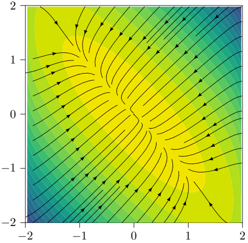
conclusion: simple algorithm performs extremely well in challenging environment

WITH DYNAMICS & DISTURBANCES TAKEN CARE OF,

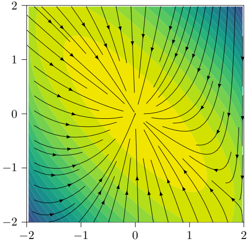
WE NOW FOCUS ON OPTIMIZATION

More general optimization flows

variable metrics

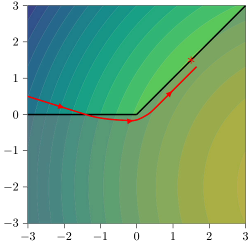


gradient: $\dot{u} = -\nabla\phi(u)$

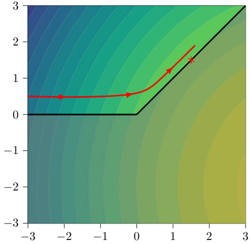


Newton: $\dot{u} = -\nabla^2\phi(u)^{-1} \cdot \nabla\phi(u)$

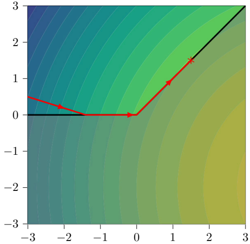
different ways of enforcing constraints



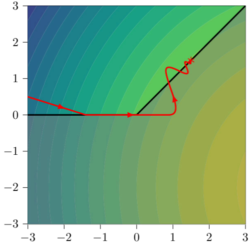
penalty function



barrier function



projected gradient flow



primal-dual saddle flow

Certificates for general optimization flows

- **variable-metric** $Q(u) \in \mathbb{S}^n_+$ gradient flow

$$\dot{u} = -\,Q(u)^{-1} \cdot \nabla\phi(u)$$

- examples: Newton method $Q(u) = \nabla^2\phi(u)$ or mirror descent $Q(u) = \nabla^2\psi(\nabla\psi(u)^{-1})$
- **stability, convergence, & feasibility** if

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

with algorithm gain $\ell \cdot \nabla h(u) \cdot \sup_u \|Q(u)^{-1}\|$

Similar results for algorithms with memory:

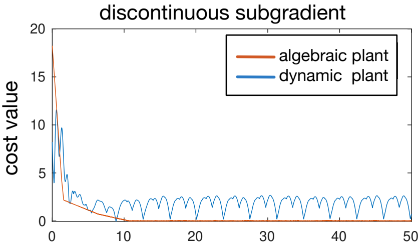
- **momentum methods** (e.g., heavy-ball)

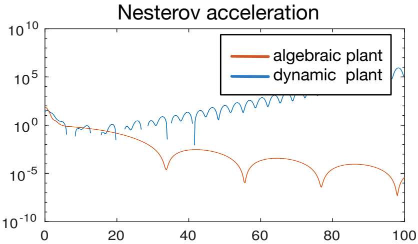
$$\ddot{u} + D(u) \cdot \dot{u} = -Q(u)^{-1} \cdot \nabla\phi(u)$$

- (exp. stable) **primal-dual saddle flows**

as long as the algorithm gain is bounded

a few **non-examples** for unbounded gain:



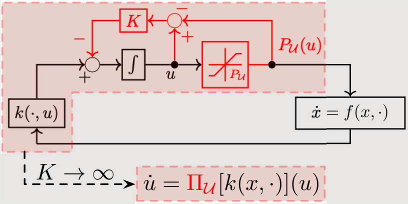


Robust implementation of projections

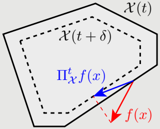
- projection & integrator → **windup**

→ **robust anti-windup** approximation

→ saturation often "for free" by physics



- disturbance → **time-varying domain**



- **temporal tangent cone** & vector field
- ensure suff. regularity & tracking certificates

→ Hauswirth et al. (2020)
"Anti-Windup Approximations of Oblique Projected Dynamical Systems for Feedback-based Optimization"

- handling **uncertainty** when enforcing **non-input constraints**: $x \in \mathcal{X}$ or $y \in \mathcal{Y}$

- **cannot measure** state x directly

→ Kalman filtering: estimation & separation

- **cannot enforce constraints** on $y = h(u)$ by projection (not actuated & $h(\cdot)$ unknown)

→ soft penalty or dualization + grad flows (inaccurate, violations, & strong assumptions)

→ project on **1st order prediction** of $y = h(u)$

$$y^+ \approx \underbrace{h(u)}_{\text{measured}} + \epsilon \underbrace{\frac{\partial h}{\partial u}}_{\text{steady-state I/O sensitivity}} \underbrace{w}_{\text{feasible descent direction}}$$

⇒ global convergence to critical points

→ Häberle et al. (2020)
"Enforcing Output Constraints in Feedback-based Optimization"

→ Hauswirth et al. (2018)
"Time-varying Projected Dynamical Systems with Applications"

COMPUTING HAPPENS IN DISCRETE TIME

$\longrightarrow$ **SAMPLED-DATA SETTING**

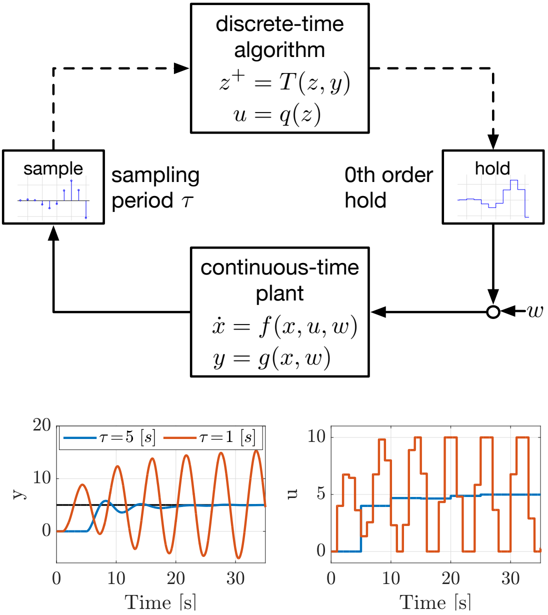
Sampled-data setting

- **continuous-time plant** :
  same assumptions as before
- **sampling** rate τ & 0th order hold
- **discrete-time algorithm** with strictly decreasing merit function & bounded gain
- examples: strongly quasi-non-expansive operator (ADMM, DR, prox, alternating projection, …)

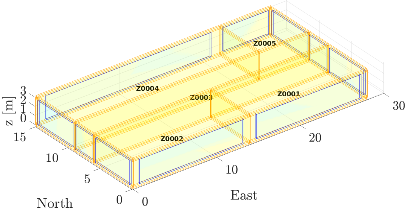
$\Rightarrow$ local / global closed-loop **ISS** if

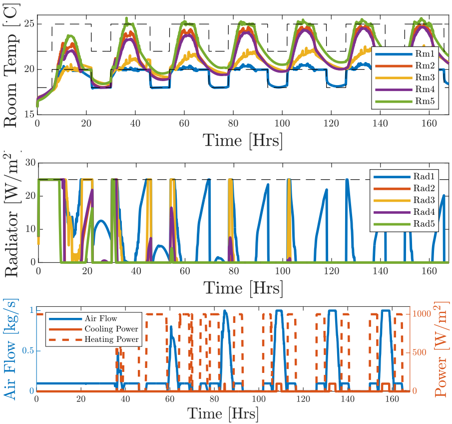
system gain $\cdot$ *algorithm gain* < 1

$\Rightarrow$ system gain decreases in τ
i.e. **sufficiently slow sampling**



Example: building temperature control





- **building model** from BRCM toolbox with 118 states (bilinear dynamics), 10 disturbances, 8 inputs, & 7 outputs
- **objective**: minimize energy cost & keep temperatures in comfort range
- **online SQP** (sequential quadratic programming) for feedback optimization
- note: algorithm is **not predictive** & doesn't use any forecast or reference

comparison to hysteresis (threshold-based) control: 32% cost reduction & 28% reduction in constraint violations

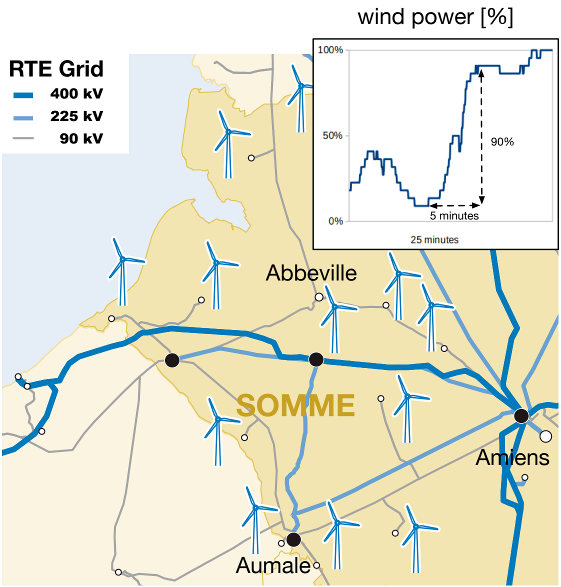
ALL ALGORITHMS REQUIRE THE GRADIENT

$$\frac{\partial}{\partial u}\phi\big(h(u),u\big) = \begin{bmatrix}\frac{\partial h}{\partial u} & \mathbb{I}\end{bmatrix} \cdot \nabla\phi(y,u)\Big|_{y=h(u)}$$

& THUS THE MODEL SENSITIVITY $\frac{\partial h}{\partial u}$ **!**

MODEL-FREE IMPLEMENTATIONS WITHOUT SENSITIVITY ?

Example: 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

- simulation of entire French grid

  → power flow + tap changer

- actuation & sensing in Blocaux

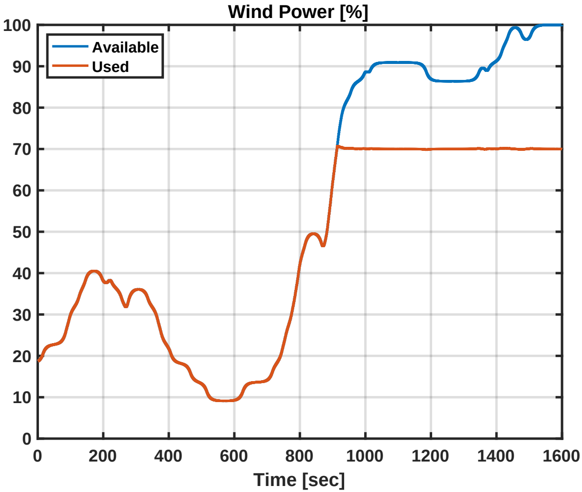
  → tap, reactive & active power

  → voltage & current magnitudes

- realistic constraints & cost

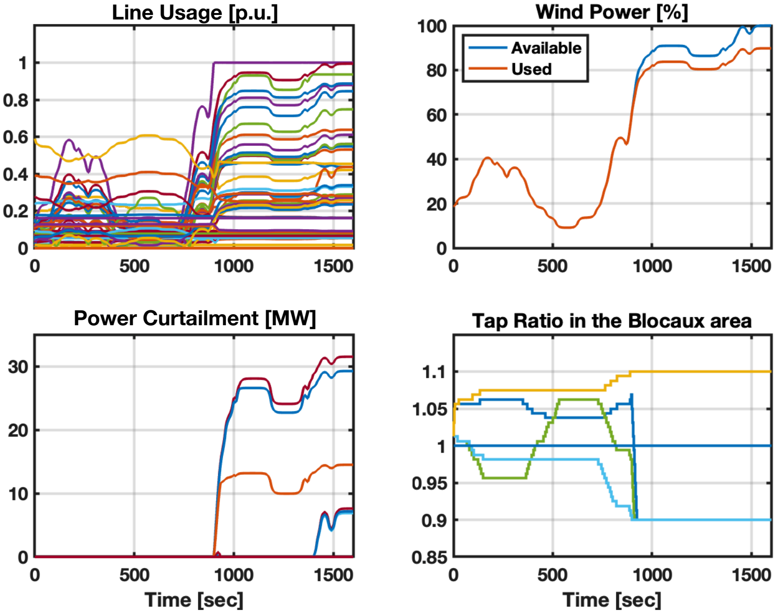
  → curtailment + losses

Current mode of operation



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

Feedback optimization using constant (wrong) sensitivity



Model-free feedback optimization

- **feedback optimization** is **robust** to inaccurate sensitivity, though the performance might be inferior

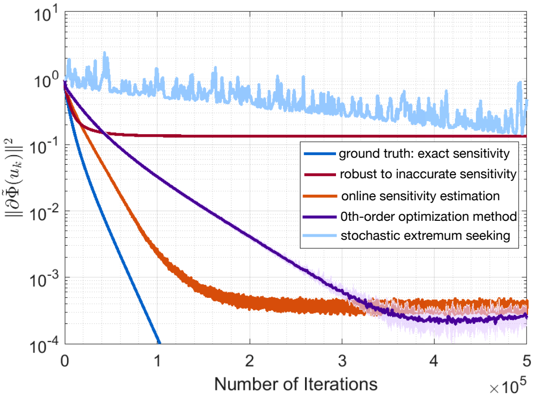
- **online sensitivity estimation** of $\frac{\partial h}{\partial u} \approx \frac{y_{t+1} - y_t}{u_{t+1} - u_t}$ via Kalman filter

- 0^{th}**-order optimization** building one-point gradient estimates

$$\frac{\partial}{\partial u}\phi(u) = \lim_{\delta \searrow 0} \mathbb{E}\left[\frac{\eta}{\delta}\phi(u + \delta \cdot \eta)\right]$$

  where η is random probing direction & δ is (small) smoothing parameter
  $\rightarrow$ constructed via single actuation

- **others**: stochastic approximation, extremum seeking, . . . do poorly



$\rightarrow$ Colombino et al. (2020) **"Towards robustness guarantees for feedback-based optimization"**

$\rightarrow$ Picallo et al. (2022) **"Adaptive Real-Time Grid Operation via Online Feedback Optimization with Sensitivity Estimation"**

$\rightarrow$ He et al. (2022) **"Model-Free Nonlinear Feedback Optimization"**

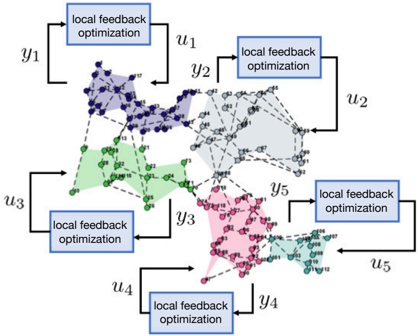
THE WORLD IS NOT AN OPTIMIZATION PROBLEM

$\longrightarrow$ **EXTENSIONS TO THE GAME-THEORETIC SETUP**

Feedback equilibrium seeking

motivation: multi-area power system

- ▶ different system operators whose cost functions are not aligned
- ▶ physical & operational coupling



- **game theory** as lingua franca:

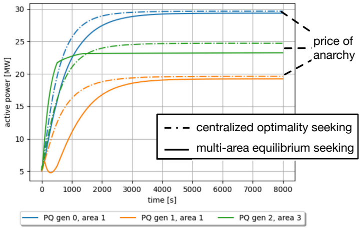
$$\min_{u_i \mathcal{U}_i} \; \phi_i(y_i, u_i)$$

  subject to constraints coupling (u_i, y_i)

- opt. solution $=$ **Nash equilibrium**
- **equilibrium-seeking algorithms** using local gradients $\frac{\partial}{\partial u_i}\phi_i(y_i, u_i)$
- similar assumptions as before &

  system gain · algorithm gain < 1

  $\Rightarrow$ **all results extend** analogously !

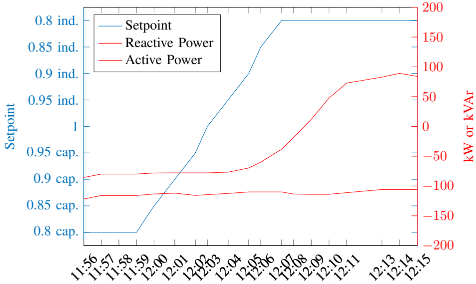


→ Belgioioso et al. (2022) **"Online Feedback Equilibrium Seeking"**

FROM LAB DEMONSTRATIONS
TO COMMERCIAL DEPLOYMENT

Deployment at Swiss utility (AEW)

- **virtual grid reinforcement** through reactive power/voltage support & power flow control
- **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**

CONCLUSIONS

Conclusions

Summary

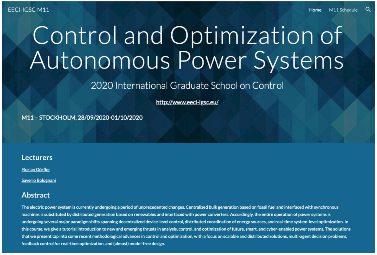
- open & online **feedback optimization** algorithms as controllers
- **unified framework** for broad class of systems, algorithms, decision-making problems, interconnection scenarios, & implementation aspects
- illustrated throughout with non-trivial **power systems** case studies
- **complete TRL scale** covered: theory $\longrightarrow$ industrial deployment

Ongoing work & open directions

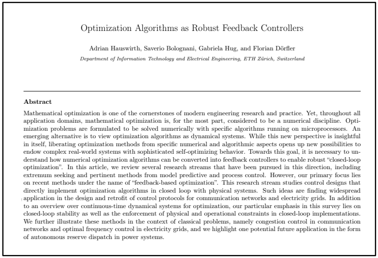
- **theory**: get rid off time-scale separation & many other extensions
- **new application domains**: supply chains & recommender systems

It works in theory and in practice !

Main resources for today



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



Optimization Algorithms as Robust Feedback Controllers

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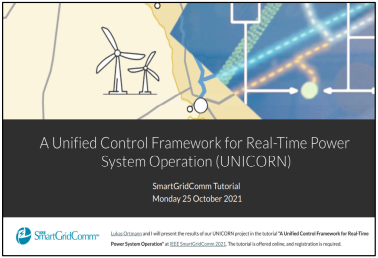
Abstract

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/

Thanks !

Florian Dörfler

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[link] to related publications