ETH zürich

AUTOMATIC CONTROL LABORATORY

A Feedback-Optimization Approach to Resilient Power System Operation

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NREL Workshop on Resilient Autonomous Energy Systems

UNICORN project
A Unified Control Framework for Real-Time Power System operation


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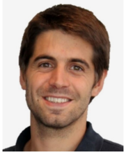
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Rte Le réseau de transport d'électricité

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Swiss Federal Office of Energy SFOE

Outline

1. Real-time power system operation
2. Feedback optimization design
3. Numerical experiments: French subtransmission grid
4. Feedback optimization for a resilient power grid
5. Conclusions

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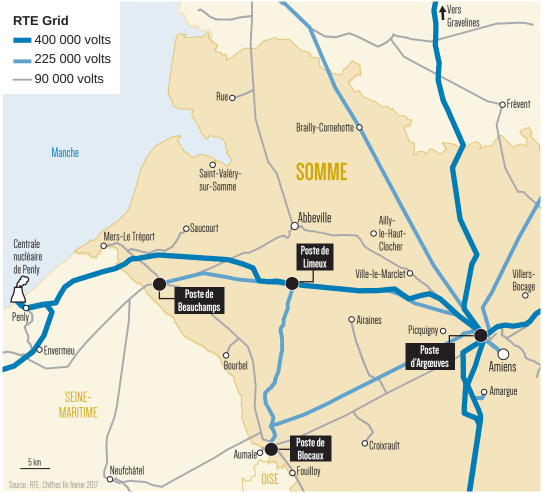
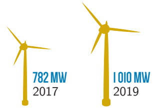
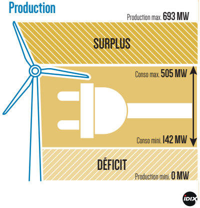
A more responsive grid is needed





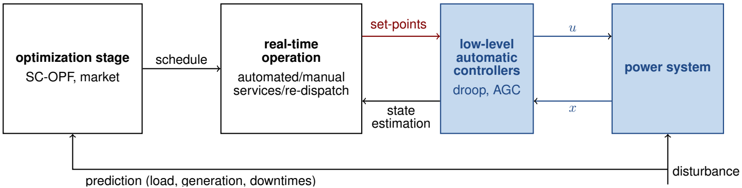


- Larger share of uncontrollable generation
- Distributed generation
- Voltage and line flow constraints

Future real-time operation

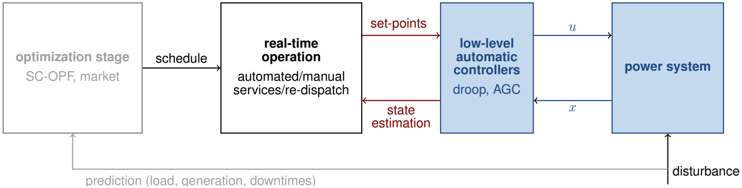
- Online monitoring and measurement
- Real-time operational specifications
- Responsive to fast disturbances

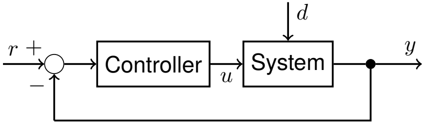
Available actuation (=set-points)



- **Active power curtailment**
  - ramp up/down limits (inverters: 0 s, wind: 20 s in emergency, 60 s otherwise)
- **AVR (Automatic Voltage Regulators) set-points**
  - example: in France, remotely adjusted every 10 s
- **Active power injection from storage**
  - Minimal delay, high flexibility
- **Reactive power injection**
  - any inverter (generators, batteries, loads), hard reactive power limits
- **Tap changers** at the substation transformers

An "autonomous" feedback control design problem



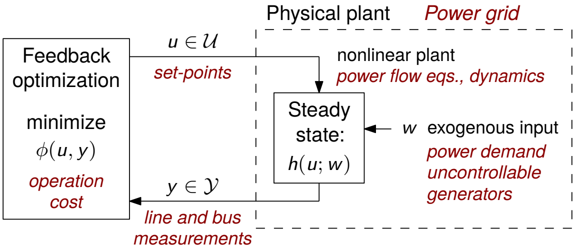


- **Steady state specifications:** solution of a constrained optimization problem
- **Schedule:** known parameter
- **Disturbance:** unknown parameters

$\rightarrow$ **Feedback optimization**

Outline

Feedback form of the OPF problem



Steady-state specifications

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

Optimization perspective

Analysis and design of algorithms with the tools of dynamical systems
but we implement them via the physics

Control perspective

Feedback systems interpreted as solvers of a specific optimization problem **but we require general objective + constraints**

Related: Self-optimizing control, economic MPC, real-time iteration, modifier adaptation, extremum seeking,...

Preprint “Optimization Algorithms as Robust Feedback Controllers” (2021)

Steady-state map $y = h(u; w)$

Chart for the $2n$-dimensional manifold of **power flow equations**:
invertible map between $\mathbb{R}^{2n}$ and a open subset of $\mathcal{M}$

Implicit function theorem

If a manifold is defined as

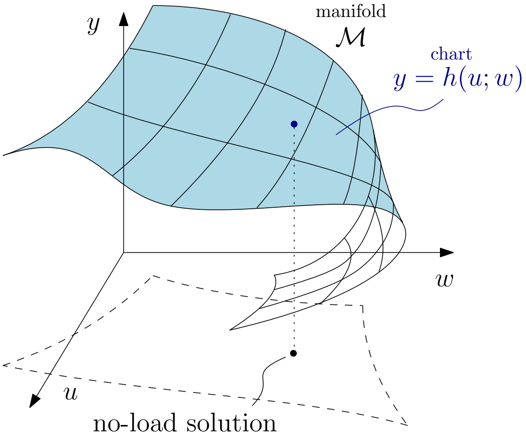
$$\mathcal{M} = \{(u, w, y) \,|\, F(u, w, y) = 0\}$$

then there exists a continuously differentiable function $y = h(u, w)$ such that

$$F(u, w, h(u, w)) = 0$$

in the open subset where

$$\nabla_y F(u, w, y) \text{ is invertible}$$



Input-output sensitivities $\nabla_{u,w} h(u, w)$

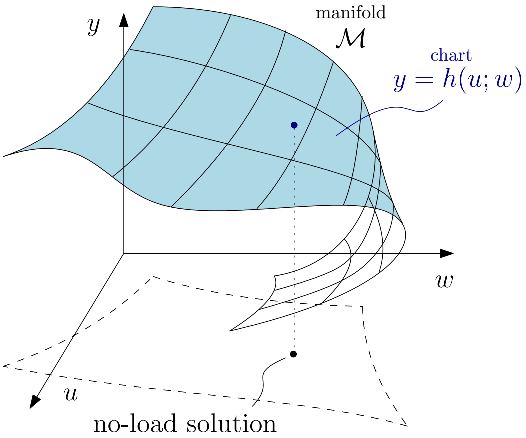
$$\nabla_{u,w} h(u, w) = -\left(\nabla_y F(u, w, y)\right)^{-1} \nabla_{u,w} F(u, w, y)$$

$\nabla_y F(u, w, y)$ is known as the power flow Jacobian and connected to

- power flow solvability
- voltage collapse

High-voltage PFM

Largest connected component of $\mathcal{M}$ that contains the **no-load solution** and where $\nabla_y F(u, w, y)$ is invertible



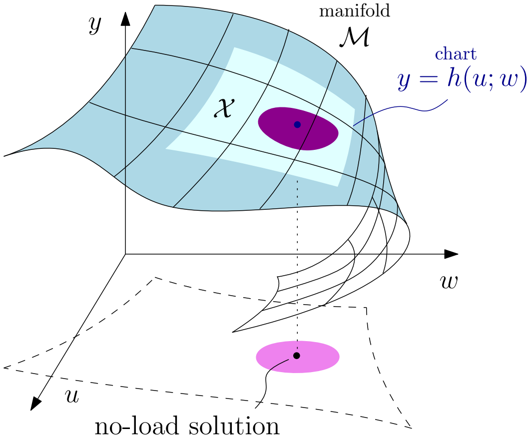
High-voltage PFM

- The high-voltage PFM $\mathcal{M}_{\text{high}}$ can rarely be derived in closed form
  - 2-bus example and little else
- **Inner approximations** are available, but they are usually **conservative**

Running assumption

The operational constraints guarantee that the state of the grid belongs to the high-voltage region

$$(\mathcal{U} \times \mathcal{Y} \times \mathcal{W}) \cap \mathcal{M} \subset \mathcal{M}_{\text{high}}$$



Design of feedback optimizers

Borrow ideas from **iterative optimization algorithms** for **non-convex optimization** and interpret these algorithms as dynamical systems

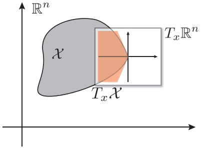
- Gradient Flows
  [Brockett, 1991], [Bloch et al., 1992], [Helmke & Moore, 1994], ...
- Interior-point methods
  [Karmarkar, 1984], [Khachian, 1979], [Faybusovich, 1992], ...
- Acceleration & Momentum methods
  [Su et al., 2014], [Wibisono et al, 2016], [Krichene et al., 2015], [Wilson et al., 2016], [Lessard et al., 2016], ...
- Saddle-Point Flows
  [Arrow et al., 1958], [Kose, 1956], [Feijer & Paganini, 2010], [Cherukuri et al., 2017], [Holding & Lestas, 2014], [Cortés & Niederländer, 2018], [Qu & Li, 2018], ...

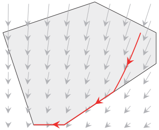
Claim: In continuous-time, most algorithms reduce to either (projected) **gradient flows** (w/o momentum) or (projected) **saddle-point** flows.

Examples of feedback optimization design

$$
\begin{aligned}
\text{minimize}_{u,y} \quad & \phi(u,y) & \\
\text{subject to} \quad & y \in \mathcal{Y} & \text{output constraints} \\
& u \in \mathcal{U} & \text{input saturation} \\
& y = h(u;w) & \text{power flow equations}
\end{aligned}
$$

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





$\mathcal{Y} \rightarrow$ Penalty function (Hauswirth 2017, Tang 2017, Mazzi 2018, ...)

Gradient descent flow $\rightarrow$ proportional-like feedback law

$$
\dot{u} = \Pi_{\mathcal{U}}\Big[-\nabla_u \phi(u,y) - \underbrace{\nabla h(u;w)'}_{\text{model}} \nabla_y \phi(u,y) - \underbrace{\nabla h(u;w)'}_{\text{model}} \nabla p(y) \Big]
$$

$\rightarrow$ **arbitrarily small output constraint violation**

Examples of feedback optimization design

$$\begin{aligned} \text{minimize}_{u,y} \quad & \phi(u,y) \\ \text{subject to} \quad & y \in \mathcal{Y} \quad \text{output constraints} \\ & u \in \mathcal{U} \quad \text{input saturation} \\ & y = h(u;w) \quad \text{power flow equations} \end{aligned}$$

Output constraint representation

$$\mathcal{Y} := \{y \mid g(y) \leq 0\}$$

Lagrangian

$$\mathcal{L}(u,y,\lambda) = \phi(u,y) + \lambda' g(y)$$

Saddle flow (Bolognani 2015, Dall'Anese 2018, Bernstein 2019, Colombino 2020, ...)

Primal descent / dual ascent → proportional-integral feedback law

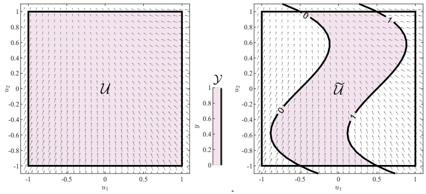
$$\begin{cases} \dot{u} = \Pi_{\mathcal{U}} \Big[-\nabla_u \phi(u,y) - \underbrace{\nabla h(u;w)'}_{\text{model}} \nabla_y \phi(u,y) - \underbrace{\nabla h(u;w)'}_{\text{model}} \nabla g(y)' \lambda \Big] \\ \dot{\lambda} = \Pi_{\geq 0} \left[g(y) \right] \end{cases}$$

→ **asymptotic (exact) constraint satisfaction**

Examples of feedback optimization design

$$\begin{aligned} \text{minimize}_{u,y} \quad & \phi(u,y) & \\ \text{subject to} \quad & y \in \mathcal{Y} & \text{output constraints} \\ & u \in \mathcal{U} & \text{input saturation} \\ & y = h(u;w) & \text{power flow equations} \end{aligned}$$

$$\tilde{\mathcal{U}} = \mathcal{U} \cap h^{-1}(\mathcal{Y})$$



Projected gradient descent (Hauswirth 2016, Häberle 2020, ...)

Projection on the input and output constraints

$$\dot{u} = \Pi_{\tilde{\mathcal{U}}}\Big[-\nabla_u \phi(u,y) - \underbrace{\nabla h(u;w)'}_{\text{model}} \nabla_y \phi(u,y) \Big]$$

→ **any-time constraint satisfaction**

Projected gradient flow via repeated Quadratic Programming

Continuous-time flow

$$\dot{u} = \Pi_{\tilde{\mathcal{U}}}\Big[-\nabla_u \phi(u,y) - \underbrace{\nabla h(u;w)'}_{\text{model}} \nabla_y \phi(u,y) \Big]$$

Assumption

$$\mathcal{U} := \{u \in \mathbb{R}^p \,|\, Au \le b\}$$
$$\mathcal{Y} := \{y \in \mathbb{R}^n \,|\, Cy \le d\}$$

Discrete-time approximation

$u^+ = u + \delta u$ where

$$\begin{aligned} \delta u := \quad & \arg\min_v \quad \| v - (-\nabla_u \phi(u,y) - \nabla h(u;w)' \nabla_y \phi(u,y)) \|^2 \\ & \text{subject to} \quad A(u + v) \le b \\ & \qquad\qquad\quad \underbrace{C(y + \nabla h(u;w)' v) \le d}_{\text{1st order approx of } h^{-1}(\mathcal{Y}) \text{ centered at the measurement } y}, \end{aligned}$$

Theorem: V. Häberle et al., "Non-convex Feedback Optimization with Input and Output Constraints," 2020

LICQ + Lipschitz + differentiability + small $\rightarrow$ global convergence to the set of local minima

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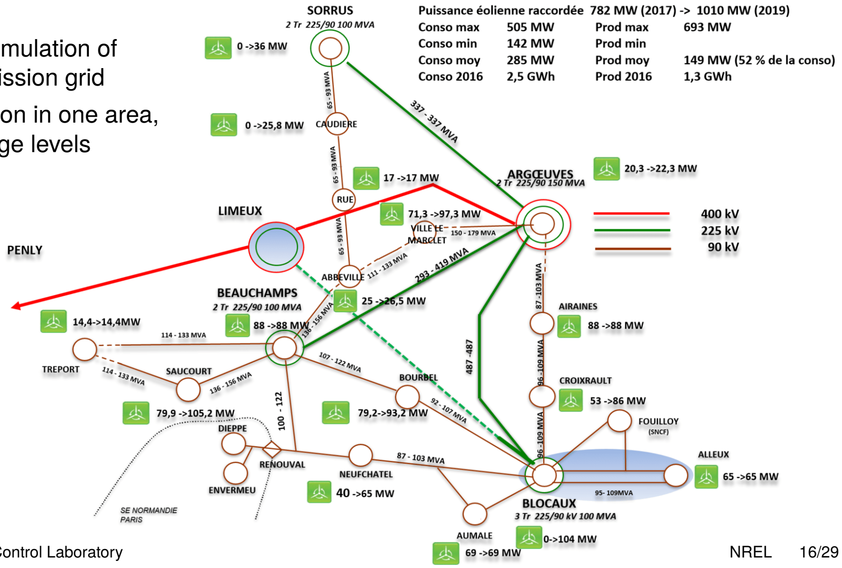
Benchmark (soon to become public)

Quasi-steady state simulation of entire French transmission grid

Goal: avoid congestion in one area, across different voltage levels



Problem specifications

Inputs

Uncontrollable

- Distributed wind generation (historical worst-case ramp)

Controllable

- Transformers tap-changer position
- Wind generators reactive power injection
- Active power curtailment

Scenario: 225kV-90kV transformer offline

Other scenarios: no tap changers, tighter constraints, higher generation, ...

Output

- real-time area state estimation

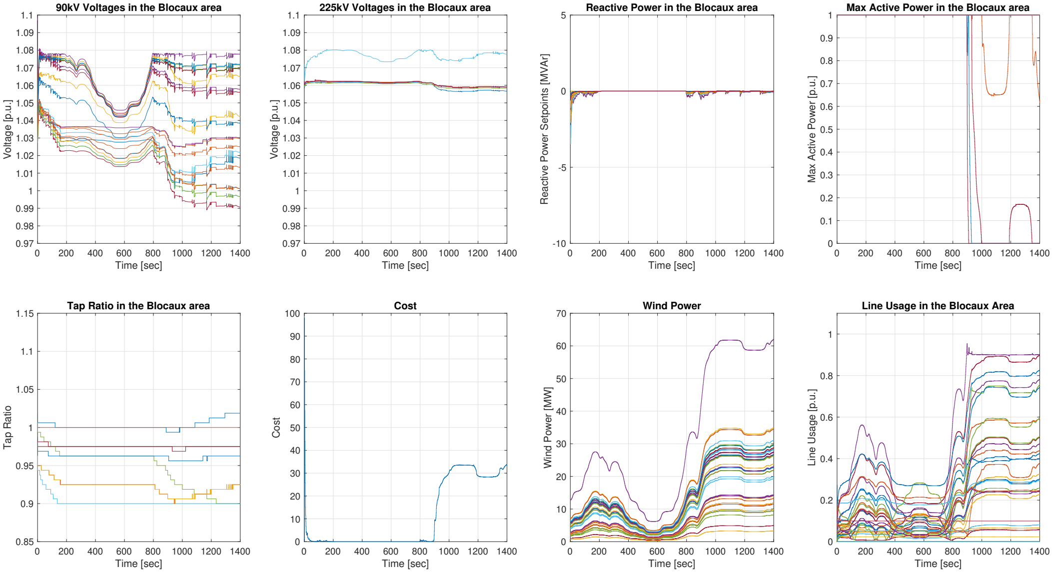
Constraints

- bus voltage limits
- line current limits
- generator limits
- tap changes

Cost

$$$ Active power curtailment

$ Power losses


90kV Voltages in the Blocaux area
Voltage [p.u.]
Time [sec]
225kV Voltages in the Blocaux area
Voltage [p.u.]
Time [sec]
Reactive Power in the Blocaux area
Reactive Power Setpoints [MVAr]
Time [sec]
Max Active Power in the Blocaux area
Max Active Power [p.u.]
Time [sec]
Tap Ratio in the Blocaux area
Tap Ratio
Time [sec]
Cost
Cost
Time [sec]
Wind Power
Wind Power [MW]
Time [sec]
Line Usage in the Blocaux Area
Line Usage [p.u.]
Time [sec]

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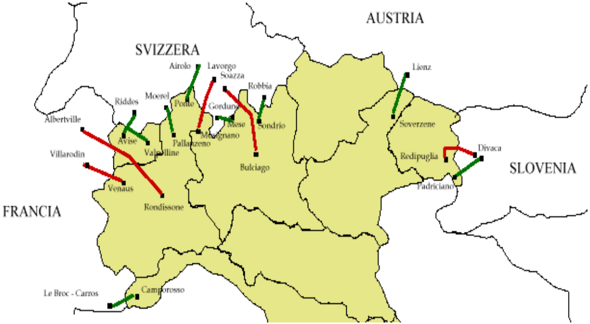
How about emergencies?

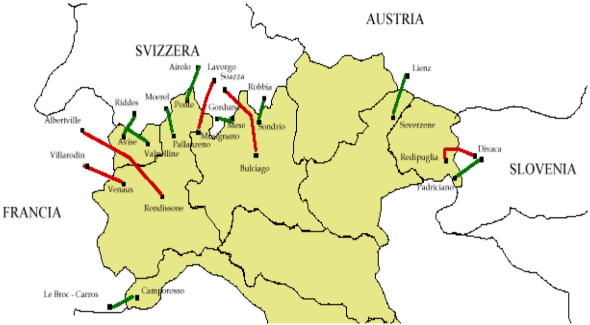


→ Overview of the events and causes of the 2003 Italian blackout

03:01	Trip of the 380 kV line Mettlen Lavorgo (CH). Attempts to reclose the line automatically until 3.03:50. Manual re-closure fails at 3:03:50.
03:02-03:08	Attempts to reclose the Mettlen-Lavorgo line. Information exchanges between ETRANS and ATEL and EGL dispatchers.
03:10	ETRANS, by phone, requests a reduction of 300 MW in Italian imports to scheduled values.
03:18-03:22	Exchange of information ETRANS - ATEL –EGL; changes in topology of the Swiss system.
03:21	Italian imports are reduced to 6400 MW
03:25	Trip of the Sils-Soazza 380 kV line (CH)
03:25	Trip of the Airolo Mettlen 220 kV line (CH)

→ 1.2 billion EUR

How about emergencies?



→ Overview of the events and causes of the 2003 Italian blackout

Can we frame emergency grid operation as a feedback optimization problem?

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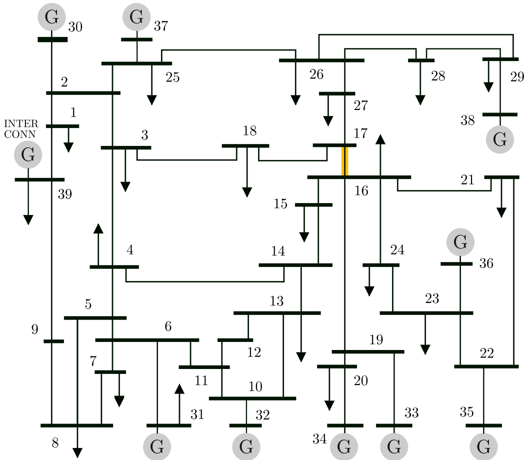
Numerical experiment IEEE 39 test grid



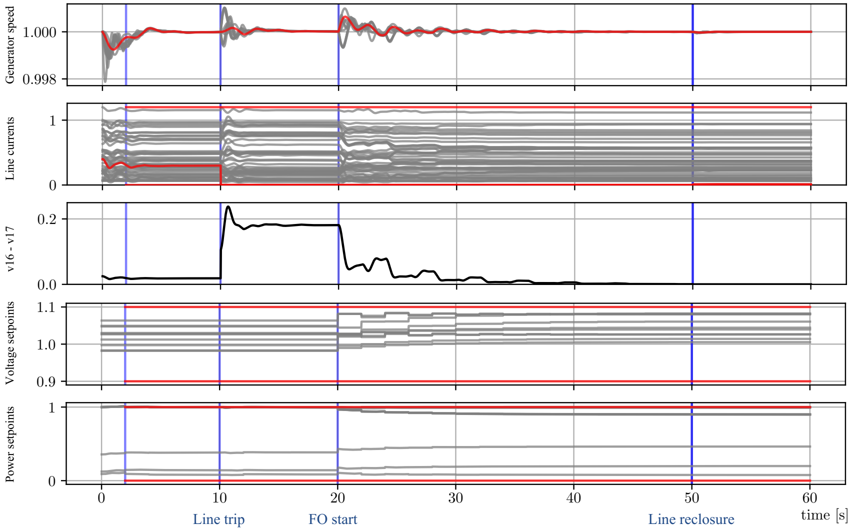
- **Fault:** Line trip of line 16-17
- **Goal:** Reclosure before cascading failure
- Line reclosure requires **small voltage difference** at the breaker

FO formalization

$$
\begin{aligned}
\min_{P_G, V_G} \quad & \|v_{16} - v_{17}\|^2 \\
\text{subject to} \quad & 0 \leq P_{G_i} \leq P_{G_i}^{\max} \\
& V_{G_i}^{\min} \leq V_{G_i} \leq V_{G_i}^{\max} \\
& v^{\min} \leq v_i \leq v^{\max} \\
& 0 \leq f_{ij} \leq f_{ij}^{\max}
\end{aligned}
$$

Full dynamic simulation

DynPSSimPy (by Gianni Hotz)



Feedback optimization for emergencies

The problem is... it shouldn't work!

Grid dynamics not at steady-state between set-point updates

- Design/certify stable interconnections (LTI systems)
  Lawrence, Simpson-Porco, Mallada, *"Linear-convex optimal steady-state control"*, 2020
  Colombino, Dall'Anese, Bernstein, *"Online opt. as a feedback controller: stability and tracking,"* 2018
  Bianchin et al. *"Time-varying optimization of LTI systems via projected primal-dual gradient flows,"* 2021
- **Quantify sufficient time-scale separation (nonlinear grid dynamics)**

Wrong (pre-fault) model during contingency

- Rely on the inherent robustness of feedback optimization (performance tradeoff)
  Colombino, Simpson-Porco, Bernstein, *"Towards robustness guarantees for feedback-based opt.,"* 2019
  L. Ortmann et al., *"Experimental validation of feedback optimization in power distribution grids,"* 2020
- **Online sensitivity estimation**

Time-scale separation analysis

A. Hauswirth, S. Bolognani, G. Hug, F. Dörfler, IEEE TAC, 2021

Optimization Dynamics

The cost function $\phi(u, x)$ has

- compact level sets
- L-**Lipschitz** gradient.

Unconstrained gradient descent

$$\dot{u} = - \quad \big(-\nabla_u \phi(u, x) - \nabla h(u; w)' \nabla_y \phi(u, x)\big)$$

Plant Dynamics

Exponentially stable system

$$\dot{x} = f(x, u; w) \quad \text{(steady state } x = h(u; w)\text{)}$$

with Lyapunov function $W(u, x)$ such that

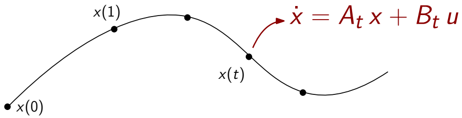
$$\dot{W}(u, x) \leq - \quad \|x - h(u; w)\|^2$$
$$\|\nabla_u W(u, x)\| \leq \zeta \|x - h(u; w)\|\,.$$

Then, all trajectories converge to the set of KKT points whenever

$$< \frac{}{\zeta L}\,.$$

(Similar results for projected gradient, saddle flow, Newton flow. **Not** for subgradient, accelerated gradient.)

Numerical evaluation at multiple linearization points



- solve **Lyapunov eq.** $A_t^\top P_t + P_t A_t \preceq I$
- **Lyapunov fcn.** $W(u,x) = \|x - h(u)\|_{P_t}^2$
- $\dot{W}(u,x) \leq -\|x - h(u)\|^2$ $(\rightarrow \quad = 1)$
- **Linear steady state** $h(u) = Hu$
- $\zeta = \|P_t H\|$

$$\rightarrow \quad \leq \frac{1}{L\|P_t H\|}$$

Plant Dynamics

Exponentially stable system

$$\dot{x} = f(x,u;w) \quad \text{(steady state } x = h(u;w)\text{)}$$

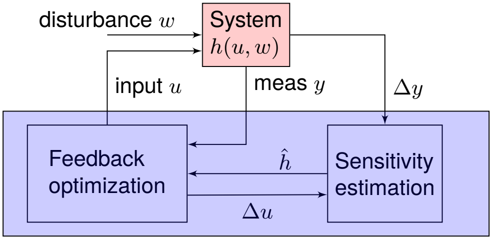
with Lyapunov function $W(u,x)$ such that

$$\dot{W}(u,x) \leq - \quad \|x - h(u;w)\|^2$$
$$\|\nabla_u W(u,x)\| \leq \zeta \|x - h(u;w)\| \, .$$

\+ bound on relatively uniform in x

\- very conservative certificate

Online sensitivity estimation



Best online estimate

$$\hat{h}_{t+1} = \arg\min_{\hat{h}} \; \hat{h} - \hat{h}_t \;^{2}_{\frac{\Sigma_t^{-1}}{\|\Delta u_t\|_2^2}} + \; \Delta y_t - U_{\Delta,t}\hat{h} \;^{2}_{\frac{\Sigma_{m,t}^{-1}}{\|\Delta u_t\|_2^2}}$$

$\rightarrow$ Kalman-like update

$$\hat{h}_{t+1} = \hat{h}_t + K_t(\Delta y_t - U_{\Delta,t}\hat{h}_t)$$

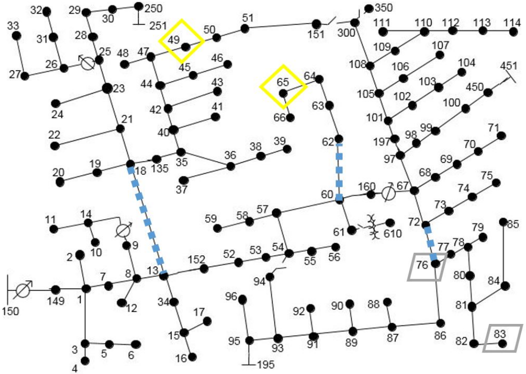
$$\Sigma_{t+1} = \big(1 - K_t U_{\Delta,t}\big)\Sigma_t + \Sigma_{p,t}\|\Delta u_t\|_2^2,$$

Proposition

Strong-monotonicity of the optimization flow + **persistently exciting** input $u_t \Rightarrow$

$$\lim_{t\to\infty} \|\mathbb{E}[h_t - \hat{h}_t]\|_2^2 \to 0 \qquad \lim_{t\to\infty} \mathbb{E}[\|h_t - \hat{h}_t\|_2^2] \to C_h < \infty \qquad \lim_{t\to\infty} \mathbb{E}[\|u_t - u^*(d_t)\|_2^2] \to C_u \leq \ldots$$

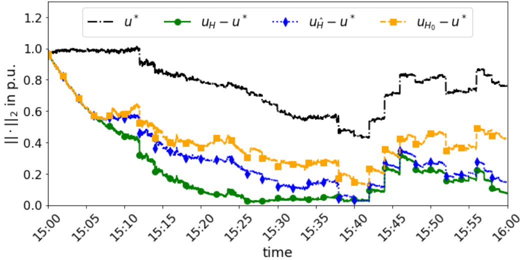
Numerical experiment



IEEE 123 test case with

- modified line impedance
- nonlinear regime

→ **time-varying steady-state sensitivity**



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Highlights

- **Real-time operation of power systems** can be automated via **feedback optimization**
  - UNICORN numerical testbed will be published soon
- Feedback optimization design taps into **iterative nonlinear optimization algorithms**
- **Numerical experiments** show that feedback optimization can produce complex multi-input/multi-objective responses to contingencies
- **Open problem 1:** tighter stability certificates for the interconnected systems
  - design guidelines
  - uniform in the system working point
- **Open problem 2:** online sensitivity estimate
  - model-free design
  - robustness to unforseen system changes

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