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A feedback approach to real-time power system operation

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Joint work with

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Including results by

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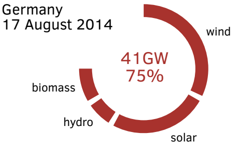
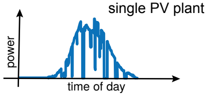
New challenges and opportunities

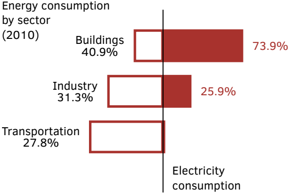
- **Fluctuating renewable energy sources**
  - poor short-range prediction
  - correlated uncertainty

- **Inverter-based generation**
  - control flexibility
  - decreased resilience
  - tighter operating specifications

- **Electric mobility**
  - large additional demand
  - new spatial-temporal patterns

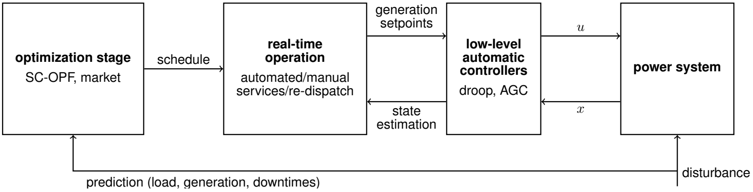




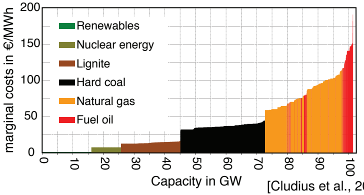


How does the grid cope with this uncertainty?

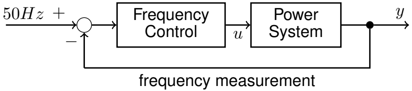
Example: power systems load / generation balancing



- **optimization stage**
  economic dispatch based on predictions/markets
- **real-time operations**
  unforeseen deviations from schedule (e.g. congestion)
- **low-level automatic control**
  frequency regulation at the individual generators

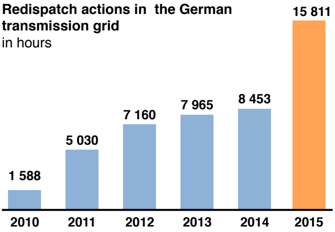


[Cludius et al., 2014]

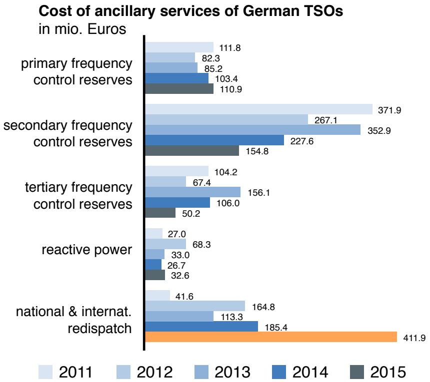


Real-time operations

- **operator-mediated** and based on **pre-defined remedial actions**
- struggles to cope with **increased uncertainty**
- today's architecture becomes highly **inefficient**



[Bundesnetzagentur, Monitoringbericht 2016]



[Bundesnetzagentur, Monitoringbericht 2016]

Ancillary services

- Real time balancing (supply = demand)
- Economic re-dispatch
- Voltage regulation
- Voltage collapse prevention
- Line congestion relief
- Reactive power compensation
- Losses minimization

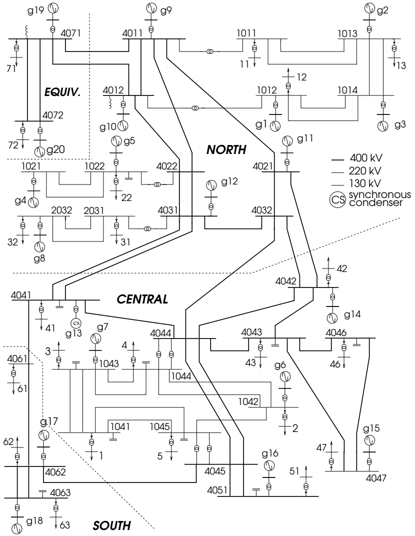
Today: **partially automated** services, provided by **separate mechanisms**.

Future real-time operation

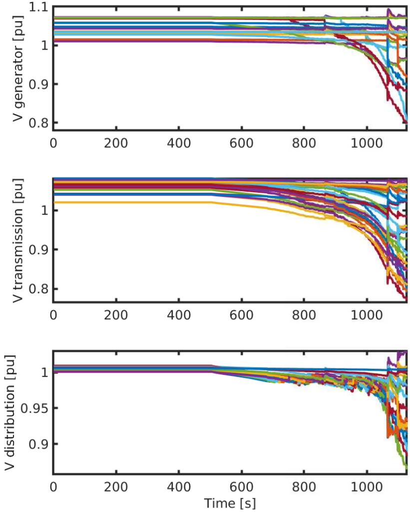
Future power systems will require faster operation, based on online monitoring and measurement, in order to meet operational specifications in real-time.

Teaser: voltage stability in the Nordic system

- Heavily loaded system
- Large transfers between north and central areas
- All loads equipped with LTCs
- Generators equipped with Automatic Voltage Regulators and Over Excitation Limiters
- Frequency control through speed governors



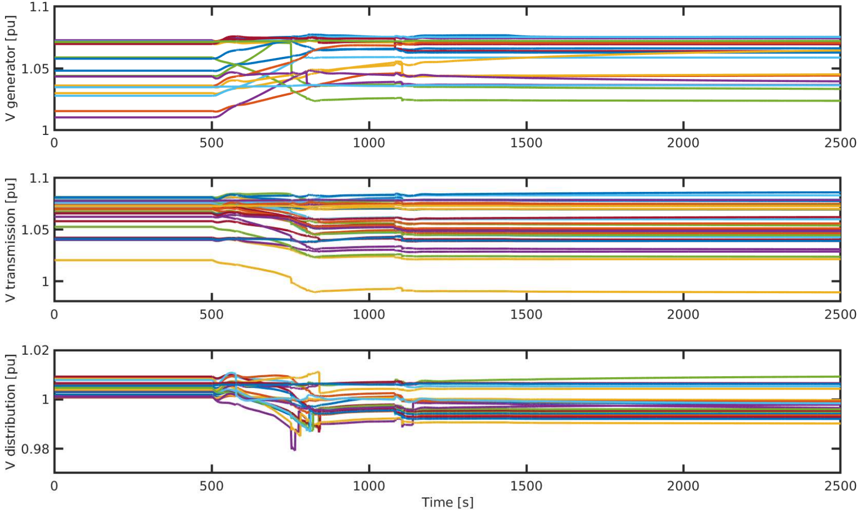
Voltage collapse



- 250 MW load ramp from $t = 500$ to $t = 800$.
- Extra demand is balanced by primary frequency control
- Cascade of activation of over-excitation limiters
- LTCs increase power demand of distribution buses
- ...voltage collapse

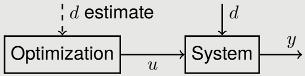
Let us assume we can control AVR set-points in real time...

Voltage collapse averted!



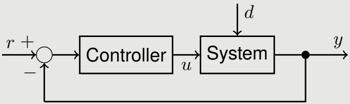
What makes real-time operation effective

Feedforward optimization



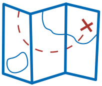
- **complex optimal decision**
- **operational constraints**
- **MIMO (multi-input/output)**
- highly model-based
- computationally intensive

Feedback control



- **robust to model uncertainty**
- **fast response**
- **measurement driven**
- suboptimal operation
- unconstrained operation

Proposal: a **feedback** approach to **optimal** real-time operation
to inherit the best of the two worlds

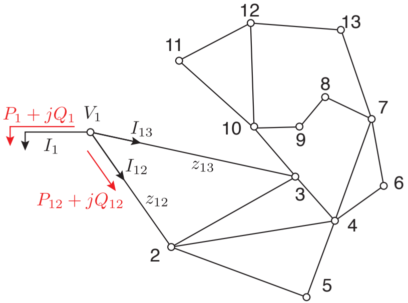


OVERVIEW

1. Projected gradient flow on the power flow manifold
2. Interconnected dynamics and stability analysis
3. Numerical experiments

PROJECTED GRADIENT FLOW ON THE POWER FLOW MANIFOLD

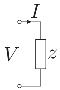
Steady-state AC power flow model



V_k nodal voltage
I_k current injection
P_k, Q_k power injections

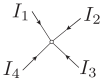
z_{kl} line impedance
I_{kl} line current
P_{kl}, Q_{kl} power flow

Ohm's Law



$V = zI$

Current Law



$0 = I_1 + \ldots + I_k$

AC power $S = P + jQ = VI^*$

AC power flow equations

$$S_k = \sum_{l \in N(k)} \frac{1}{z_{kl}^*} V_k (V_k^* - V_l^*) \quad \forall k \in \mathcal{N}$$

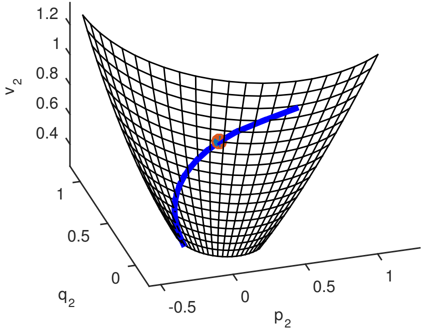
(all variables and parameters are $\mathbb{C}$-valued)

Power flow manifold

- State $x = \begin{bmatrix} v \\ \theta \\ p \\ q \end{bmatrix}$
- AC power flow equations $f(x) = 0$
- Set of all grid states that satisfy the **AC power flow equations**

$$\rightarrow \textbf{ power flow manifold} \quad \mathcal{M} := \{x \mid f(x) = 0\}$$

- Regular submanifold of dimension $2n$

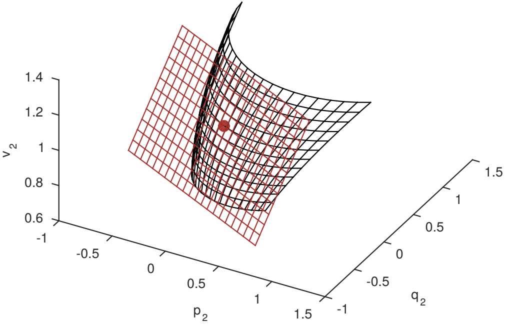


Trajectory feasibility

- Closed-loop trajectories necessarily belong to $\mathcal{M}$

$\Rightarrow$ $\dot{x}$ is tangent to $\mathcal{M}$

Tangent space



Tangent space at a given power flow solution $x^* \in \mathcal{M}$

$$A_{x^*}(x - x^*) = 0$$

$$A_{x^*} := \left. \frac{\partial f(x)}{\partial x} \right|_{x=x^*}$$

- **Implicit** – No input/outputs (not a disadvantage)
- **Sparse** – The matrix A_{x^*} has the sparsity pattern of the grid graph
- **Structure preserving** – Elements of A_{x^*} depend on local parameters
- Useful **approximation** for power system analysis

$\rightarrow$ Bolognani & Dörfler (2015)
“Fast power system analysis via implicit linearization of the power flow manifold”

Control specifications as an OPF

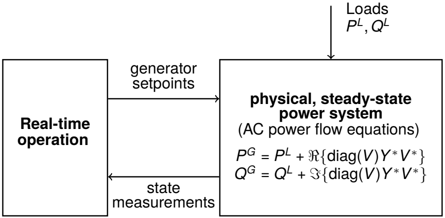
Real-time Optimal Power Flow (OPF)

- Minimize cost of generation
- Satisfy AC power flow laws
- Respect generation capacity
- No over-/under-voltage
- No congestion

$$\begin{aligned}
\text{minimize} \quad & \sum_{k\in\mathcal{N}} \text{cost}_k(P_k^G) \\
\text{subject to} \quad & P^G + jQ^G = P^L + jQ^L + \text{diag}(V)Y^*V^* \\
& \underline{P}_k \le P_k^G \le \overline{P}_k, \quad \underline{Q}_k \le Q_k^G \le \overline{Q}_k \\
& \underline{V}_k \le V_k \le \overline{V}_k \\
& |P_{kl} + jQ_{kl}| \le \overline{S}_{kl}
\end{aligned}$$

Challenging **specifications on the closed-loop trajectories**:

1. stay on the manifold at all times
2. satisfy constraints at all times
3. converge to the OPF solution



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& \underline{V}_k \leq V_k \leq \overline{V}_k \\
& |P_{kl} + jQ_{kl}| \leq \overline{S}_{kl}
\end{aligned}
$$

Prototype of real-time OPF

$$
\begin{aligned}
\text{minimize} \quad & \phi(x) \\
\text{subject to} \quad & x \in \mathcal{K} = \mathcal{M} \cap \mathcal{X}
\end{aligned}
$$

$\phi : \mathbb{R}^n \to \mathbb{R}$ objective function

$\mathcal{M} \subset \mathbb{R}^n$ AC power flow equations

$\mathcal{X} \subset \mathbb{R}^n$ operational constraints

Projected dynamical systems for trajectory feasibility

Operational constraints

$$x(t) \in \mathcal{K} = \mathcal{M} \cap \mathcal{X} = \{\text{power flow manifold}\} \cap \{\text{operational constraints}\}$$

$$\dot{x} = \Pi_{\mathcal{K}} \left(x, -\text{grad}\, \phi(x)\right), \qquad x(0) = x_0$$

where $\Pi_{\mathcal{K}}(x, v) \in \arg \min_{w \in T_x \mathcal{K}} ||v - w||$ belong to the **feasible cone** $T_x\mathcal{K}$

Theorem [AH et al. 2016] (simplified)

If ϕ has compact level sets on $\mathcal{K}$, then the (Carathéodory-)solution $x(t)$ will converge to a critical point x^* of ϕ on $\mathcal{K}$.
Furthermore, if x^* is asymptotically stable then it is a local minimizer of ϕ on $\mathcal{K}$.

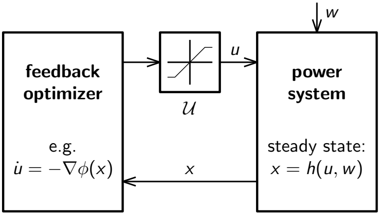
→ Hauswirth, Bolognani, Hug, & Dörfler (2016)
"Projected gradient descent on Riemanniann manifolds with applications to online power system optimization"

How to induce the projected gradient flow

- Algebraic constraints on the state x
  - **Implicit:** power flow equations $f(x) = 0$
  - **Explicit:** steady state of local controllers + physics $x = h(u, w)$

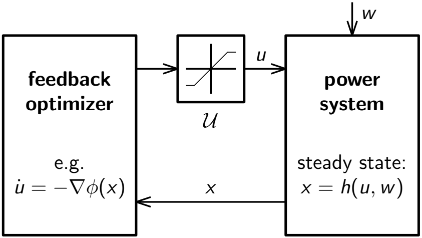
Equivalent optimization problem

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



- **Input saturation:** $u \in \mathcal{U}$ at all times (hard constraint)
- **Closed-loop trajectory:** $h(u, w) \in \mathcal{X}$ at all times (soft constraint)
- **Steady state:** The closed-loop system converges to the solution of the OPF

Online optimization in closed loop



Optimization perspective

Algorithms as dynamical systems

[Lessard et al., 2014], [Wilson et al., 2018]

→ **implemented via the physics**

Control perspective

Existing feedback systems interpreted as solving opt. problem

→ **general objective + constraints**

Lots of recent theory development:

[Bolognani et. al, 2015], [Dall'Anese et al., 2014], [Gan and Low, 2016], [Tang and Low, 2017], [Cady et al., 2015], [Hauswirth et al. 2016], . . . **survey: [Molzahn et al. 2018]**

INTERCONNECTED DYNAMICS AND STABILITY ANALYSIS

Problem Description

Optimization Problem

$$\underset{y,u}{\text{minimize}} \quad \Phi(x)$$

$$\text{subject to} \quad x = (CH + D)u + CRw$$

$$u \in \mathcal{U}$$

Steady-state feedback design:

$$\dot{u} = \Pi_{\mathcal{U}} \left(-\epsilon (CH + D)^T \nabla \Phi\right)(u)$$

LTI Dynamics

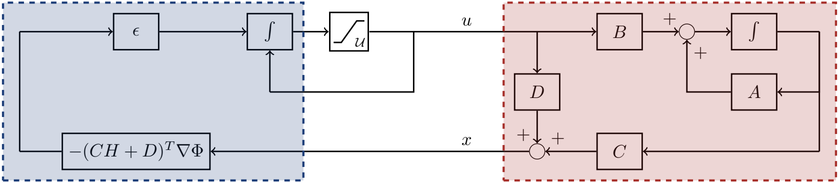
$$\dot{z} = Az + Bu + Qw$$

$$x = Cz + Du$$

A is Hurwitz, steady-state maps

$$z = \underbrace{-A^{-1}B}_{H}\, u \underbrace{-A^{-1}Q}_{R}\, w$$

$$x = (CH + D)u + CRw$$



Main Result

Theorem

Assume

- LTI system internally asymptotically **stable**: $\exists P \succ 0 : \; PA + A^T P \preceq -\mathbb{I}$
- $\widehat{\Phi}(u) := \Phi((CH + D)u + Rw)$ has
  - **compact level sets**
  - **ℓ-Lipschitz** gradient

Then, the closed-loop system is stable & converges to critical points for all

$$0 \leq \epsilon \leq \frac{1}{2\ell \|PH\|}$$

Proof: based on singular perturbation analysis, performed via an *ad hoc* La Salle argument.

$\rightarrow$ Menta, Hauswirth, Bolognani, Hug & Dörfler (2018)
“Stability of Dynamic Feedback Optimization with Applications to Power Systems”

Highlights and comparison of our contributions

Weak assumptions on plant

- Internal stability

→ Steady-state map H (reduced model dependency)

→ No assumptions on observability or controllability

Weak assumptions on cost

- Lipschitz gradient

→ No convexity required

- **Convexity** $\Rightarrow$ global convergence

- Potentially conservative bound, but

→ **minimal assumptions** on optimization problem & plant

→ directly **useful for design** (no LMI/IQC stability test)

[Nelson et al. 2017], [Colombino et al. 2018]

- proof is general and **can be extended** to other algorithms

→ applicable to switched systems ($\rightarrow$ input saturation)

NUMERICAL EXPERIMENTS

Optimal constrained frequency control

Dynamic model:

- linearized swing dynamics (with primary frequency control)
- 1st-order turbine-governor
- DC power flow approximation (Kron-reduced)

$$\left.\begin{aligned} \dot\theta &= \omega \\ \dot\omega &= -M^{-1}\left(D\omega + \mathbf{B}\theta - p + p^L(t)\right) \\ \dot p &= -K\left(R^{-1}\omega + p - p^C\right) \end{aligned}\right\}$$

$$\dot z = Az + Bu + Qw \quad \text{where}$$

$$z = \begin{bmatrix}\theta\\ \omega\\ p\end{bmatrix},\ u = p^C,\ w = p^L(t)$$

Measurement: frequency at node 1 + line flows + active power injections

$$x = \begin{bmatrix} \mathbb{0} & 1 & 0 & \dots & 0 & \mathbb{0} \\ \mathbf{B}^\ell & & & \mathbb{0} & & \mathbb{0} \\ \mathbb{0} & & & \mathbb{0} & & I \end{bmatrix} z$$

Power application: optimal constrained frequency control

Optimization problem:

$$\begin{aligned} \underset{x,u}{\text{minimize}} \quad & \Phi(x) \\ \text{subject to} \quad & x = CHu + CRw \\ & u \in \mathcal{U} \end{aligned}$$

where $x = CHu + CRw$ is the steady-state input-output map and

$$\Phi(x) = \text{cost}(x) + \tfrac{1}{2}\|\max\{0, \underline{x} - x\}\|_{\Xi}^2 + \tfrac{1}{2}\|\max\{0, x - \overline{x}\}\|_{\Xi}^2$$

encodes both

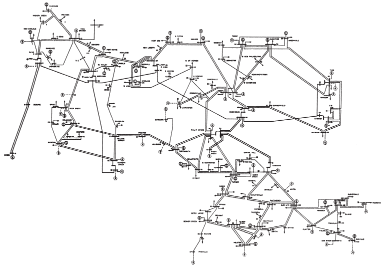
- **economic cost** of p (DC OPF)
- **operational limits** (on line flows, frequency, ...) as penalty functions

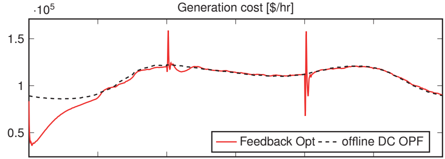
while

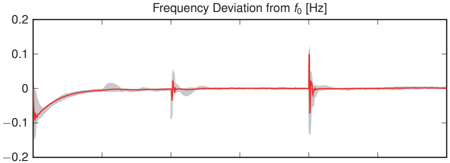
- $\mathcal{U}$ describes the **saturation constraints** on the actuation.

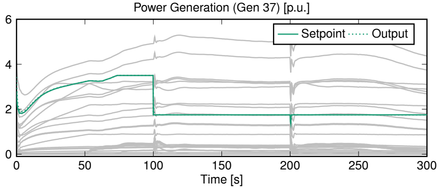
Response to contingencies

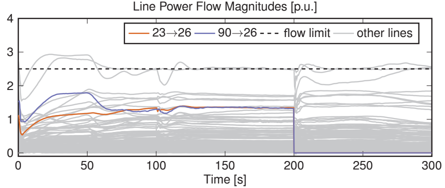
Generator outage & double line tripping in IEEE 118-bus test system







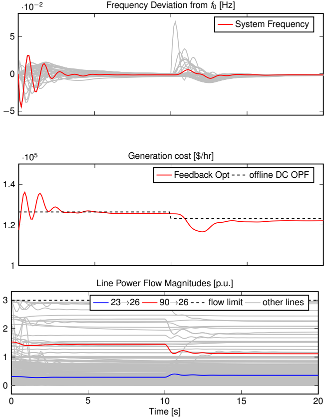




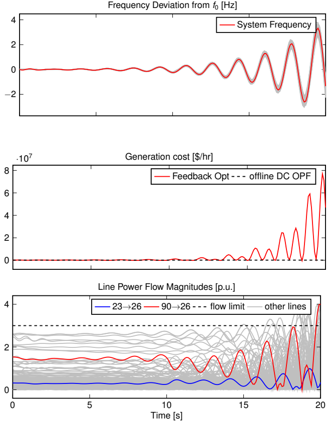
How conservative is $\varepsilon^\star$?

Simulation on IEEE 118-bus test case

still **stable for** $\varepsilon = 2\varepsilon^\star$



unstable for $\varepsilon = 10\varepsilon^\star$



Note: Observed factors of conservativeness ranging from 1.2 to 1000, depending on penalty scalings

Conclusions

- Integral **feedback control** to to solve constrained optimization problems
- A sound mathematical framework: **projected dynamical systems**
  - existence of solutions, time varying constraints, disconnected regions, ...
- The proposed **design methods** features
  - completely general objective functions and constraints
  - robustness to model mismatch / rejection of unmeasured disturbances
  - almost-model-free design (only steady-state map is needed)
  - quantifiable robustness guarantees w.r.t. system dynamics

$\rightarrow$ a new approach to **real-time power system operation**

UNICORN A Unified Control Framework for Real-Time Power System Operation

ETH zürich Rte

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