Control of Low-Inertia Power Systems: Naive & Foundational Approaches

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Acknowledgements



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Foundation

ЕТН



FNSNF FONDS NATIONAL SUISSE SCHWEIZERISCHER NATIONALFONDS FONDO NAZIONALE SVIZZERO

C. Arghir











T. Borsche



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Frequency of West Berlin when re-connecting to Europe Source: Energie-Museum Berlin 50.1 December 7, 1994 Ηz 50.1 50. 49.9 49.90 (9.85-

UCTE

400

300.

before re-connection: islanded operation based on batteries & single boiler afterwards connected to European grid based on synchronous generation

*10 sec

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49.80



Operation centered around bulk synchronous generation





Fundamental challenge: operation of low-inertia systems

We slowly loose our giant electromechanical low-pass filter:

$$\sqrt{\frac{d}{dt}}\omega(t) = P_{\text{generation}}(t) - P_{\text{demand}}(t)$$

$$(\overbrace{M}^{\theta, \ \omega})$$

change of kinetic energy = instantaneous power balance



Berlin curves before and after re-connecting to Europe Source: *Energie-Museum Berlin*



Low-inertia stability: # 1 problem of distributed generation





frequency violations in Nordic grid
 (source: ENTSO-E)

same in Switzerland (source: Swissgrid)

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inertia is shrinking, time-varying, localized, ... & increasing disturbances

Solutions in sight: none really ... other than **emulating virtual inertia** through fly-wheels, batteries, super caps, HVDC, demand-response, ...

Virtual inertia emulation

devices commercially available, required by grid-codes, or incentivized through markets

IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 28, NO. 2, MAY 2013			
Improvement of Transient Response	Implementing Virtual Inertia in DFIG-Based		
Nimish Soni, Student Member, IEEE, Suryanarayana Doolla, Member, IEEE, and Mikul C Chandrotar. Member IEEE	Wind Power Generation		
Virtual synchronous generators: A survey and new perspective	ves Dynamic Frequency Control Support: a Virtual		
Hassan Bevrani ^{a,b,*} , Toshifumi Ise ^b , Yushi Miura ^b	Inertia Provided by Distributed Energy Storage		
^a Dept. of Electrical and Computer Eng., University of Kurdistan, PO Box 416, Sanandaj, Iran ^b Dept. of Electrical, Electronic and Information Eng., Osaka University, Osaka, Japan	to Isolated Power Systems		
IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 28, NO. 2, MAY 2013	authier Delille, Member, IEEE, Bruno François, Senior Member, IEEE, and Gilles Malarange		
Inertia Emulation Control Strategy f	or Grid Tied Converter with Virtual Kinetic		
VSC-HVDC Transmission Systems	Storage		
Jiebei Zhu, Campbell D. Booth, Grain P. Adam, Andrew J. Roscoe, and Chris G.	Bright M.P.N van Wesenbeeck ¹ , S.W.H. de Haan ¹ , Senior member, IEEE, P. Varela ² and K. Visscher ³ ,		

- $\mathbf{M} \frac{d}{dt} \omega(t) = P_{\text{generation}}(t) P_{\text{demand}}(t) \approx \text{derivative control on } \omega(t)$
- \Rightarrow focus today: where to do it? how to do it properly? what else?

Introduction

Outline

- **Optimal Placement of Virtual Inertia** network, disturbances, & performance metrics matter
- Proper Virtual Inertia Emulation Strategy maybe we should not think about frequency and inertia
- A Foundational Control Approach restart from scratch for low-inertia systems

Conclusions



optimal placement of virtual inertia









(sub)optimize performance and see what we learn



Test case

- inertia emulation control via PLL & batteries: $u_{i} = \begin{bmatrix} \tilde{M}_{i} & \tilde{D}_{i} \end{bmatrix} x_{PLL,i}$ $d \longrightarrow \dot{x} = Ax + Bu + Gd$ $u \qquad u_{i} = \begin{bmatrix} \tilde{M}_{i} & \tilde{D}_{i} \end{bmatrix} x_{PLL,i}$
- dynamics: swing equation, droop via governor & turbine, and PLL



Algorithmic approach to desperate & non-convex problem

- structured state-feedback with constraints on gains
- computation \mathcal{H}_2 norm, gradient, & projections:

 $\rightarrow y_{perf}$

 X_{PII}



• observability and controllability Gramians via Lyapunov equations

$$(A - BK)^{\top}P + P(A - BK) + Q + K^{\top}RK = 0$$
$$(A - BK)L + L(A - BK)^{\top} + GG^{\top} = 0$$

2
$$\mathcal{H}_2$$
 norm $J = \text{Trace}(G^{\top}PG)$ and gradient $\nabla_K J = 2(RK - B^{\top}P)L$

- **3** projection on structural constraint: $\nabla_{\tilde{M},\tilde{D}}J = \prod_{\tilde{M},\tilde{D}}[\nabla_{K}J]$
- \Rightarrow \tilde{M} and \tilde{D} can be optimized by first-order methods, IPM, SQP, etc.



placement & metrics matter! can we get analytic insights ?

Inertia placement in swing equations

• simplified network swing equation model:



 decision variable is inertia: m_i ∈ [m_i, m_i] (additional nonlinearity: enters as m_i⁻¹ in constraints & objective) 21/38

Closed-form results for cost of primary control



(computations show that insights *roughly* generalize to other costs)

allocation: the primary control effort \mathcal{H}_2 optimization reads equivalently as

$$\begin{array}{ll} \underset{m_i}{\text{minimize}} & \sum \\ \text{subject to} & \sum \\ m_i \end{array}$$

 $\sum_{i} \overline{m_{i}}$ $\sum_{i} m_{i} \leq m_{bdg}$ $m_{i} \leq m_{i} \leq \overline{m_{i}}$

key take-away is disturbance matching:

• optimal allocation $m_i^{\star} \propto \sqrt{t_i}$ or $m_i^{\star} = \min\{m_{\text{bdg}}, \overline{m_i}\}$

 $\Rightarrow\,$ disturbance profile known from historic data, but rare events are crucial

- suggests **robust** $\min_m \max_t$ **allocation** to prepare for worst case
- \Rightarrow valley-filling solution: $t_i^{\star}/m_i^{\star} = const.$ (up to constraints)

Robust min-max allocation for three-area case study Original, Robust, and Capacity allocations Cost Scenario: fault (impulse) can occur at any single node disturbance set $T \in \mathbb{T} = \{\mathbb{e}_1 \cup \cdots \cup \mathbb{e}_{12}\}$ \Rightarrow min/max over convex hull ► inertia capacity constraints allocation subject to capacity constraints Original, Robust, and Uniform allocations Cost robust inertia allocation outperforms heuristic max-capacity allocation ► results become **intuitive**: valley-filling property same for uniform allocation allocation subject to the budget constraint

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Standard power electronics control would continue by







Model matching (\neq emulation) as inner control loop

$$i_{dc} \bigoplus_{v_{dc} \ g_{dc} \$$

matching control:
$$\dot{\theta} = \eta \cdot v_{dc}$$
, $m = \hat{m} \cdot \begin{bmatrix} -\sin(\theta) \\ \cos(\theta) \end{bmatrix}$ with $\eta, \hat{m} > 0$

- $\Rightarrow \text{ matched machine with inertia } M = \frac{C_{dc}}{\eta^2}, \text{ droop/dissipation } D = \frac{G_{dc}}{\eta^2}, \text{ torque } \tau_m = \frac{i_{dc}}{\eta}, \text{ field current } i_f = \frac{\hat{m}}{\eta L_m}, \text{ \& imbalance signal } \omega = \eta \cdot v_{dc}$
- \Rightarrow pros: uses physical storage, uses DC measurements, & remains passive $$_{\rm 28/38}$$



Further properties of machine matching control

- stationary P vs. $(|V|, \omega)$ nose curves reveal $(P, \omega, |V|)$ droop slopes
- ② base for outer loops
- $\Rightarrow i_{dc} = \mathsf{PID}(v_{dc}) \text{ gives}$ virtual inertia & damping
- reformulation as virtual
 & adaptive oscillator:

$$\dot{m} = \eta \, v_{dc} \cdot \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} m$$

(we'll later find out that this is a profound insight)



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Proving the obvious (?)

• steady-state locus: physics & desired closed-loop vector field coincide (point-wise in time) on set

$$\mathcal{S} := \left\{ (x, u, \omega_0) : f_{\mathsf{phys}}(x, u) = f_{\mathsf{des}}(x, \omega_0) \right\}$$

- control-invariance: steady-state operation $(x, u, \omega_0) \in S$ for all time if and only if
 - **()** synchronous frequency ω_0 is constant
 - **2** at each **generator**: constant torque τ_m & excitation i_f
 - **3** at each **inverter**: constant DC current i_{dc} & inverter duty cycle with constant amplitude & synchronous frequency: $\dot{m} = \omega_0 \cdot \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} m$
 - **③ network** satisfies power flow equations with impedances $R + \omega_0 JL$
 - \Rightarrow explicit feedforward input-to-steady-state map



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3 reformulation via relative angles δ with respect to synchronous motion

OC/AC time-scale separation via singular perturbation arguments

slow DC variables: $x_r = (\theta, \omega, i_f, \theta_I, v_{dc}),$ $\dot{x}_r = f_z(x_r, z_{\alpha,\beta}, u)$ fast AC variables: $z_{\alpha,\beta} = (i_s, i_I, v, i_T),$ $\epsilon \dot{z}_{\alpha,\beta} = f_{\alpha,\beta}(x_r, z_{\alpha,\beta}, u)$

1 rotating coordinate frame with synchronous frequency ω_0

• internal oscillator model for inverter duty cycle with inputs ω_m , \hat{m}

 $\dot{\theta}_I = \omega_m, \quad m = \hat{m} \begin{bmatrix} -\sin(\theta) \\ \cos(\theta) \end{bmatrix}$

Inearization around unique steady-state

 \Rightarrow time scales of AC quantities scaled by $1/\omega_0$

• model reduction steps

Reduction to a tractable model for synthesis

Insights from reduced model: $v_{dc} \propto$ power imbalance

• nonlinear reduced order model in rotating frame:

$$\begin{split} \dot{\theta} &= \omega \\ M\dot{\omega} &= -D\omega + \tau_m - \tau_e(x_r, u) \\ L_f \dot{i}_f &= -R_f i_f + v_f - v_{EMF}(x_r, u) \\ \dot{\theta}_I &= \omega_m \\ C_{dc} \dot{v}_{dc} &= -G_{dc} v_{dc} + i_{dc} - i_{sw}(x_r, u) \end{split}$$

- interconnection via τ_e , i_{sw} , v_{EMF}
- analogies & interpretation:

generator	inverter	interpretation	
$\frac{1}{2}M\omega^2$	$\frac{1}{2}C_{dc}v_{dc}^2$	energy stored in device	
$ au_{m}$	i _{dc}	energy supply	
$ au_e$	i _{sw}	energy flow to grid	
ω	V _{dc}	power imbalance	25 / 20
			30 / 30

MIMO converter/generator control architecture

• decentralized converter/generator controls







Conclusions on virtual inertia emulation

Where to do it?

- $\textcircled{0} \mathcal{H}_2 \text{-optimal (non-convex) allocation}$
- **2** numerical approach via gradient computation
- O closed-form results for cost of primary control

How to do it?

- $\textcircled{0} \quad \text{down-sides of naive inertia emulation}$
- 2 novel machine matching control
- reveals power imbalance visible in DC voltage

What else to do?

- first-principle low-inertia system model
- In nonlinear steady-state control specifications
- **③** reduction to tractable model for synthesis
- ${f 0}$ first promising controllers ... to be continued

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appendix



Low inertia issues have been broadly recognized by TSOs, device manufacturers, academia, funding agencies, etc.

MIGRATE project: Massive InteGRATion of power Electronic devices



"The question that has to be examined is: how much power electronics can the grid cope with?" (European Commission)



optimization of practically relevant power system engineering metrics

The practical engineering metrics for low-inertia systems

disturbance inputs:

• **step** (loss of load/generation)

• impulse (line open-/closing)

• **noise** (renewables & loads)

performance outputs:

- overshoot (peak signals after fault)
- **ROCOF** (rate of change of frequency)
- **spectrum** (damping ratio cones)

restoration time



- not practical for optimization & control design
- metrics & faults justified only in a system dominated by machines





accuracy of tractable low-inertia system model

Full order nonlinear vs. reduced order linearized

- two generators connected to an impedance load
- 10% increase in $au_{m,1}$ at t=0



inertia placement in swing equations



Algebraic characterization of the \mathcal{H}_2 norm

Lemma: \mathcal{H}_2 norm via observability Gramian

 $\|G\|_2^2 = \operatorname{Trace}(B^{\mathsf{T}}PB)$

where P is the observability Gramian $P = \int_0^\infty e^{A^T t} Q e^{At} dt$

- *P* solves a Lyapunov equation: $PA + A^TP + Q = 0$
- A has a zero eigenvalue \rightarrow restricts choice of Q

$$y = \begin{bmatrix} Q_1^{1/2} & 0\\ 0 & Q_2^{1/2} \end{bmatrix} \begin{bmatrix} \theta\\ \omega \end{bmatrix} \qquad Q_1^{1/2} \mathbb{1} = \mathbb{C}$$

• *P* is unique for $P[\mathbb{1}\[0\] = [0\[0\]]$

Problem formulation



where would you place the inertia?

uniform, max capacity, near disturbance?

the more inertia the better?

Building the intuition: results for two-area networks

Fundamental learnings

- explicit closed-form solution is rational function
- **2** sufficiently uniform $t_i/d_i \rightarrow$ strongly **convex** & fairly **flat** cost
- In non trivial in the presence of capacity constraints



Closed-form results for cost of primary control

$$\begin{array}{l} \mathsf{P}/\dot{\theta} \text{ primary droop control} \\ (\omega_m - \omega^*) \propto (P_i^* - P_i(\theta)) \\ & \\ & \\ D_i \dot{\theta}_i = P_i^* - P_i(\theta) \end{array}$$



(can also model effect of PSS control)

Primary control effort \rightarrow accounted for by integral quadratic cost

$$\int_0^\infty \dot{\theta}(t)^\mathsf{T} D \, \dot{\theta}(t) \, dt$$

which is the \mathcal{H}_2 performance for the penalties $Q_1^{1/2} = 0$ and $Q_2^{1/2} = D$

Primary control ... cont'd

Theorem: the primary control effort optimization reads equivalently as

 $\begin{array}{ll} \underset{m_i}{\text{minimize}} & \sum_{i=1}^n \frac{t_i}{m_i} \\ \text{subject to} & \sum_{i=1}^n m_i \leq m_{\text{bdg}} \\ & \underline{m_i} \leq m_i \leq \overline{m_i}, \quad i \in \{1, \dots, n\} \end{array}$

Key take-away is disturbance matching:

- optimal allocation $\propto \sqrt{t_i}$ or $m_i = \min\{m_{bdg}, \overline{m_i}\}$
- optimal allocation independent of network topology

Location & strength of disturbance are crucial solution ingredients

Robust inertia allocation

empirical disturbance distributions available but we want to prepare for "rare events"

 $\begin{array}{ll} \underset{P,m_{i}}{\text{minimize maximize }} & \operatorname{Trace}(B(\mathbf{t}_{i}^{1/2})^{\mathsf{T}}PB(\mathbf{t}_{i}^{1/2})) \rightarrow \operatorname{robust performance} \\ & \text{subject to} & T \in \mathbb{T} & \rightarrow \operatorname{disturbance family} \\ & t_{i} \geq 0 \forall i \& \sum_{i=1}^{n} t_{i} = 1 \rightarrow \operatorname{normalization} \\ & \text{inertia budget, capacities, } \& \operatorname{Lyapunov equation} \end{array}$ $\begin{array}{l} \\ & \text{Key insights:} \\ & \text{inner maximization problem is linear in } T \\ & \Rightarrow \min \text{-max can be converted to minimization by duality} \\ & \text{valley filling solution for primary control metric:} \end{array}$

 $t_i^{\star}/m_i^{\star} = const.$ (up to constraints)

Taylor & power series expansions

Key idea: scalar series expansion at m_i in direction μ_i :

$$rac{1}{m_i+\delta\mu_i}=rac{1}{m_i}-rac{\delta\mu_i}{m_i^2}+\mathcal{O}(\delta^2)$$

 \Rightarrow expand system matrices via **Taylor series** in direction μ :

$$\mathbf{A}(m+\delta\mu) = \mathbf{A}^{(0)}_{(m,\mu)} + \mathbf{A}^{(1)}_{(m,\mu)}\delta + \mathcal{O}(\delta^2) \quad , \quad \mathbf{B}(m+\delta\mu) = \dots$$

 \Rightarrow expand observability Gramian via **power series** in direction μ :

$$\mathbf{P}(m+\delta\mu) = P^{(0)}_{(m,\mu)} + P^{(1)}_{(m,\mu)}\delta + \mathcal{O}(\delta^2)$$

Magic happens: the Lyapunov equation decouples

$$0 = \delta^{0} \left(P^{(0)} A^{(0)} + A^{(0)\top} P^{(0)} + Q \right) + \delta^{1} \left(P^{(1)} A^{(0)} + A^{(0)\top} P^{(1)} + \left(P^{(0)} A^{(1)} + A^{(1)\top} P^{(0)} \right) \right) + \mathcal{O}(\delta^{2})$$

numerical method for the general case

Explicit gradient computation

1 nominal Lyapunov equation for $\mathcal{O}(\delta^0)$:

 $\mathsf{P}^{(0)} = \mathsf{Lyap}(\mathsf{A}^{(0)}, \mathsf{Q})$

2 perturbed Lyapunov equation for $\mathcal{O}(\delta^1)$ terms:

$$\mathbf{P^{(1)}} = Lyap(\mathbf{A^{(0)}}, \mathbf{P^{(0)}A^{(1)}} + {\mathbf{A^{(1)}}^{\top}\mathbf{P^{(0)}}})$$

3 expand objective at m in direction μ :

$$\mathsf{T}\mathsf{race}(B(m)^\mathsf{T}\mathsf{P}(m)B(m)) = \mathsf{T}\mathsf{race}((\ldots) + \delta(\ldots)) + \mathcal{O}(\delta^2)$$

3 gradient: Trace $(2 * B^{(1)^{\mathsf{T}}} P^{(0)} B^{(0)} + B^{(0)^{\mathsf{T}}} P^{(1)} B^{(0)})$

 \Rightarrow use favorite method for reduced optimization problem with explicit gradient & without Lyapunov constraint

results for a three-area case study

Modified Kundur case study: 3 areas & 12 buses transformer reactance 0.15 p.u., line impedance (0.0001+0.001i) p.u./km $\int \frac{10}{9} \int \frac{10}{9$

Heuristics outperformed by \mathcal{H}_2 - optimal allocation

Scenario: disturbance at #4

- locally optimal solution outperforms heuristic max/uniform allocation
- ▶ optimal allocation ≈ matches disturbance
- inertia emulation at all undisturbed nodes is actually detrimental
- ⇒ **location** of disturbance & inertia emulation matters



allocation subject to capacity constraints



allocation subject to the budget constraint

Eye candy: time-domain plots of post fault behavior



Robust min-max allocation

Scenario: fault (impulse) can occur at any single node

- disturbance set $T \in \mathbb{T} = \{ e_1 \cup \cdots \cup e_{12} \}$
- \Rightarrow min / max over convex hull
- robust inertia allocation outperforms heuristics
- results become more intuitive: the more inertia (capacity & budget) the better & valley-filling property



allocation subject to capacity constraints



allocation subject to the budget constraint

