

# Fast and Accurate Calculation of Dynamics Sensitivities Using a Discrete- Adjoint Approach

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# Outline

1. Sensitivity analysis for power grid simulations: local discrete adjoint sensitivity
2. Software infrastructure: Efficient implementation and accurate calculations of dynamic sensitivities
3. Applications: optimization, parameter estimation, uncertainty quantification

# Sensitivity Analysis for Dynamic Power Grid Simulations

- **Sensitivity analysis**: describe the behavior of functionals that depend on dynamic variables with respect to system parameters
- Applications: sensitivity analysis in power grid simulations:
  - Optimization: security constrained OPF, economic dispatch
  - Impact or apportionment assessment,
  - Uncertainty quantification, parameter estimation
- Two types of sensitivities: **local** and global
- Local sensitivities: **discrete** and continuous
- Local sensitivity can be computed by: finite difference, forward, and **adjoint**

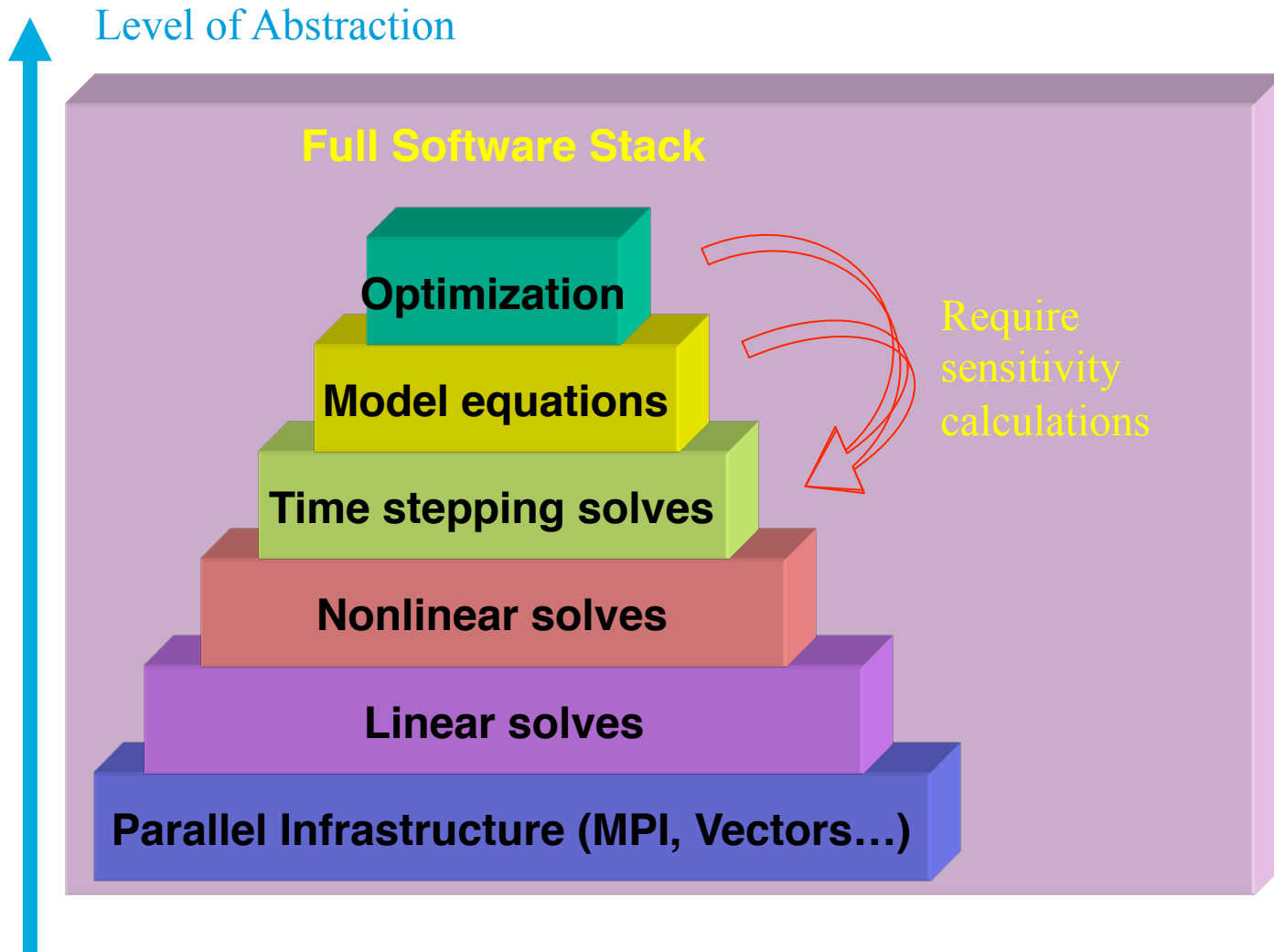
- System:  $M \frac{dy}{dt} = f(t, y, p)$

- Numerical model:  $y_{n+1} = \mathcal{N}_n(y_n)$

- Cost function, e.g.,:  $G = g(y(t_F))$

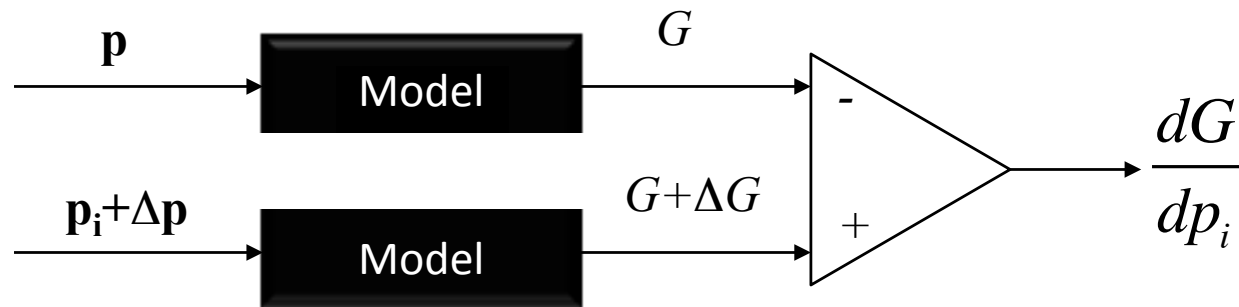
- Sensitivity:  $\mathcal{S} = \frac{dG(\cdot)}{dp}$

# Numerical Software Stack

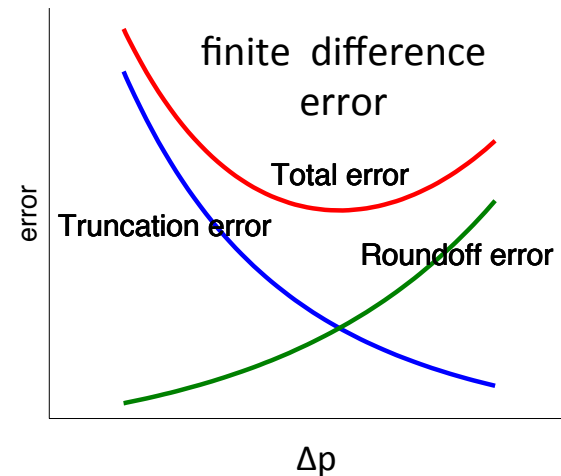


# Computing Sensitivities: Finite Differences

- Easy to implement



- Inefficient for many parameter case, due to one-at-a-time
- Error depends critically on the perturbation value  $\Delta p$



# Computing Sensitivities: The Forward Approach



- Governing equation

$$M \frac{dy}{dt} = f(t, y), \quad y(t_0) = y_0(p)$$

- Discretization with a time stepping algorithm, (e.g. backward Euler)

$$M y_{n+1} = M y_n + h (f(t_{n+1}, y_{n+1}))$$

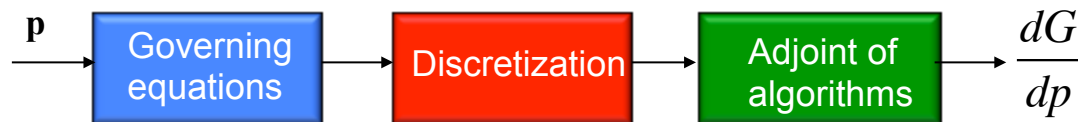
- Differentiate the equation on parameters  $\mathcal{S}_{\ell, N} = dG/dp_{\ell} = dy_N/dp_{\ell}$

$$M \mathcal{S}_{\ell, n+1} = M \mathcal{S}_{\ell, n} + h (\mathbf{f}_y(t_{n+1}, y_{n+1}) \mathcal{S}_{\ell, n+1} + \mathbf{f}_p(t_{n+1}, y_{n+1}))$$

A red dashed arrow points from the  $\mathcal{S}_{\ell, N}$  term in the previous list item to the  $\mathcal{S}_{\ell, n+1}$  term in this equation.

- Solve one full (linear) system for each parameter

# Computing Sensitivities: The Adjoint Approach



- Numerical one-step integrator:

$$y_{n+1} = \mathcal{N}_n(y_n), \quad n = 0, \dots, N - 1, \quad y_0 = \gamma(p)$$

- Enforce sensitivity equation through Lagrange multipliers, then differentiate:

$$\frac{d}{dp} \mathcal{L} = \frac{d}{dp} \left\{ G - (\lambda_0)^T (y_0 - \gamma) - \sum_{n=0}^{N-1} (\lambda_{n+1})^T (y_{n+1} - \mathcal{N}(y_n)) \right\}$$

- Solve the linear sensitivity equations for all parameters in one-shot:

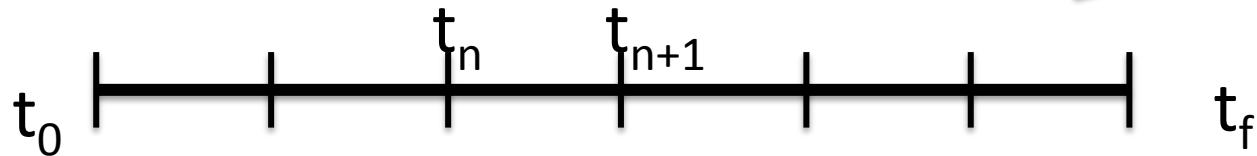
$$\lambda_N = \left( \frac{dG}{dy} \right)^T, \quad \lambda_n = \left( \frac{d\mathcal{N}}{dy}(y_n) \right)^T \lambda_{n+1}, \quad n = N - 1, \dots, 0,$$
$$\nabla_p G = \left( \frac{d\gamma}{dp} \right)^T \lambda_0$$

# Sensitivity calculations: Forward or Adjoint?

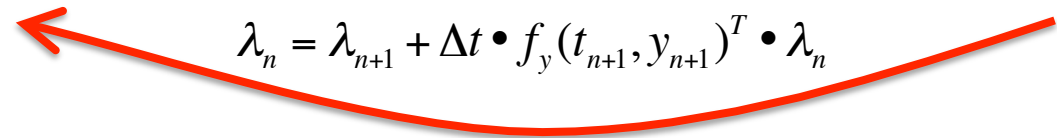
	Forward	Adjoint
Best to use when the number of	parameters $\ll$ functionals	parameters $\gg$ functionals
Complexity	$O(\# \text{ of parameters})$	$O(\# \text{ of functionals})$
Checkpointing	No	Yes
Implementation	Medium	High

Forward run and forward sensitivity

$$y_{n+1} = y_n + \Delta t \cdot f(t_{n+1}, y_{n+1})$$



$$\lambda_n = \lambda_{n+1} + \Delta t \cdot f_y(t_{n+1}, y_{n+1})^T \cdot \lambda_n$$



Reverse (adjoint) run

Hong Zhang, Shrirang S. Abhyankar, Emil M. Constantinescu, and Mihai Anitescu, "A Discrete sensitivity analysis of power system dynamics." Under Review, 2016.



# Adjoint Integration with Portable, Extensible Toolkit for Scientific Computation (PETSc)

- PETSc: Open-source numerical library for large-scale parallel computation

- Portability

- 32/64 bit, real/complex,
- single/double/quad precision
- Unix, Linux, MacOS, Windows
- C, C++, Fortran, Python, MATLAB
- GPGPUs and support for threads

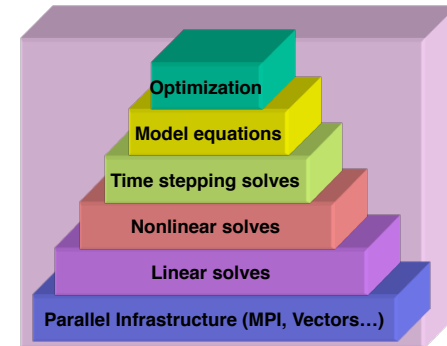
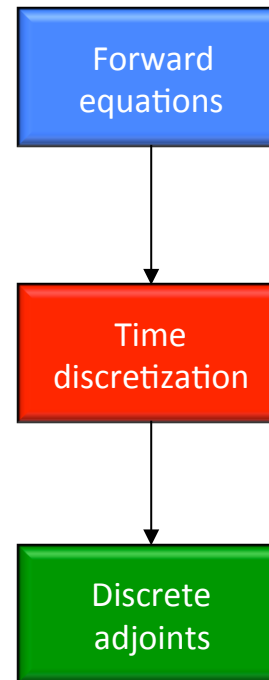
- Extensibility

- ParMetis, SuperLU, SuperLU\_Dist, MUMPS, HYPRE, UMFPACK, Sundials, Elemental, Scalapack, UMFPack, ...

- Toolkit

- Sequential and Parallel vectors
- Sequential and Parallel matrices
- **Iterative solvers and preconditioners**
- **Parallel nonlinear solvers**
- **Adaptive time stepping (ODE and DAE) solvers**

Time-stepping level  
adjoint implementation



Forward time stepping



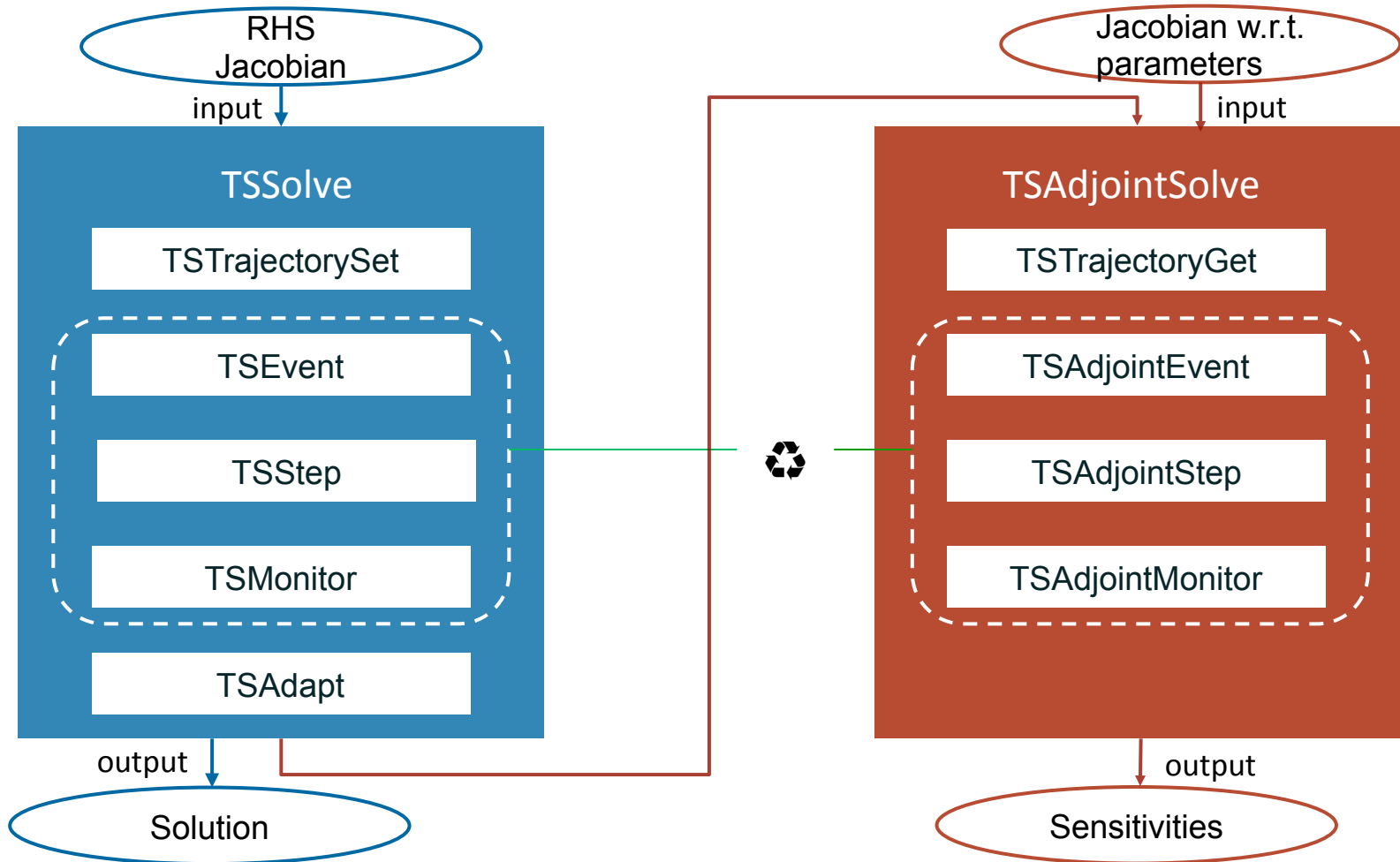
Manual  
derivation

Backward time stepping

*Hong Zhang, Shirang S. Abhyankar, Emil M. Constantinescu, and Mihai Anitescu, "A Discrete sensitivity analysis of power system dynamics." Under Review, 2016.*

# PETSc Design Goals and Implementation

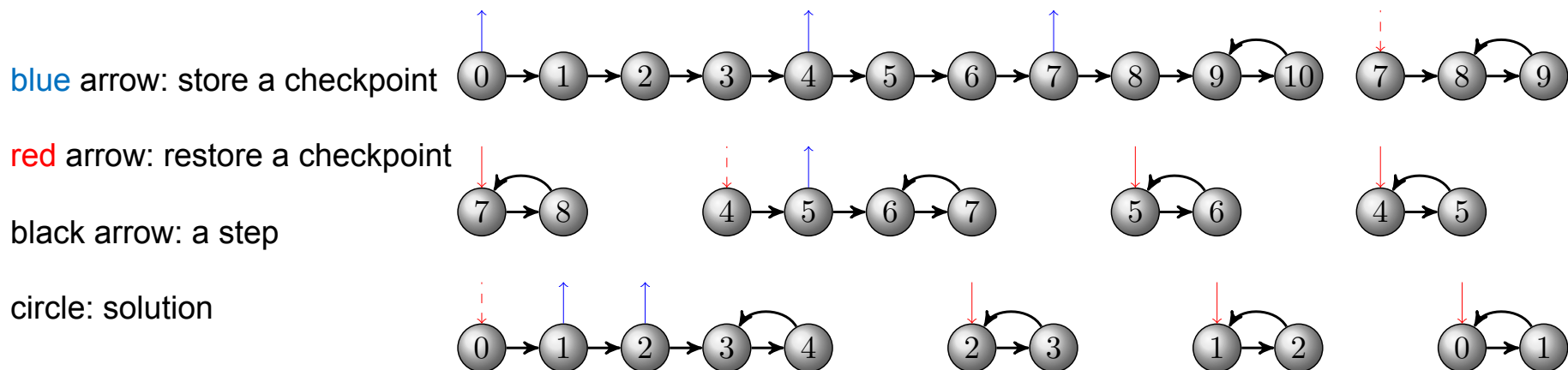
1. Minimize intrusion
2. Reuse functionalities (already implemented in PETSc or provided by users)
3. Aim for general-purpose solutions and support for switching



# Optimal Checkpointing

- Minimize the number of recomputations and the number of reads/writes by using existing library **revolve** a less intrusive way
  - revolve** is designed as a top-level controller for time stepping
  - TSTrajectory consults **revolve** about when to restore/restore/recompute
- Incorporate a variety of single-level and two-level schemes for offline and online checkpointing
  - Existing algorithms work great for RAM only checkpointing
  - Our extension is optimal for RAM+disk

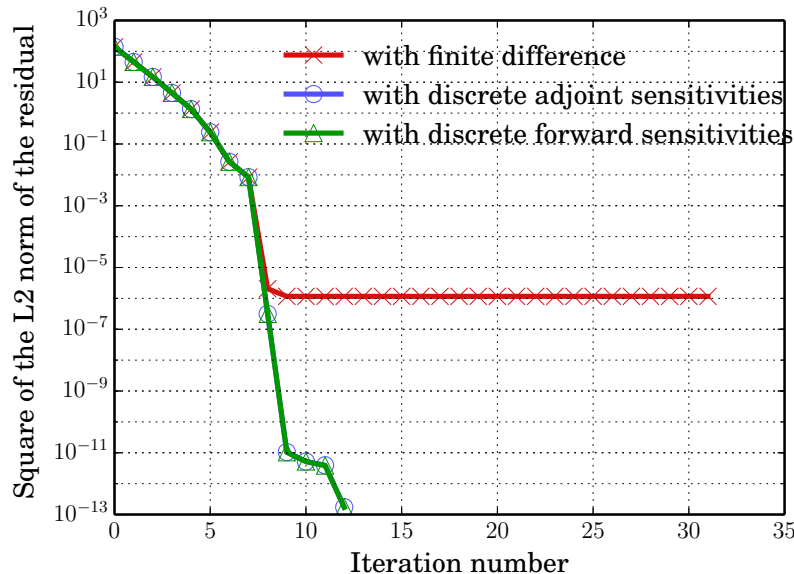
An optimal schedule given 3 allowable checkpoints in RAM:



# How Precision of the Gradients Affects Optimization

- Maximize mechanical power input, subject to the generator swing equations and a constraint on the maximum rotor angle deviation:

$$\begin{aligned} & \min_{P_m} -P_m + \sigma \int_{t_0}^{t_F} \max(0, \delta - \delta_{max})^\eta dt \\ & \text{s.t.} \\ & \frac{d\delta}{dt} = \omega_B (\omega - \omega_s) \\ & \frac{d\delta}{dt} = \frac{\omega_s}{2H} (P_m - P_{max} \sin(\delta) - D (\omega - \omega_s)) \end{aligned}$$



- optimization process using the forward and adjoint sensitivities converge after 13 iterations
- optimization using the finite-difference approximations stall with a residual of  $10^{-6}$

Hong Zhang, Shirang S. Abhyankar, Emil M. Constantinescu, and Mihai Anitescu, "A Discrete sensitivity analysis of power system dynamics." *Under Review*, 2016.

# Sensitivity of Dynamic Security Metric to System Dispatch Parameters

- Dynamic security metric for each generator

$$H_i(x, y) = \sigma \int_0^T [\max(0, \omega_i - \omega^+, \omega^+ - \omega_i)]^\eta dt$$

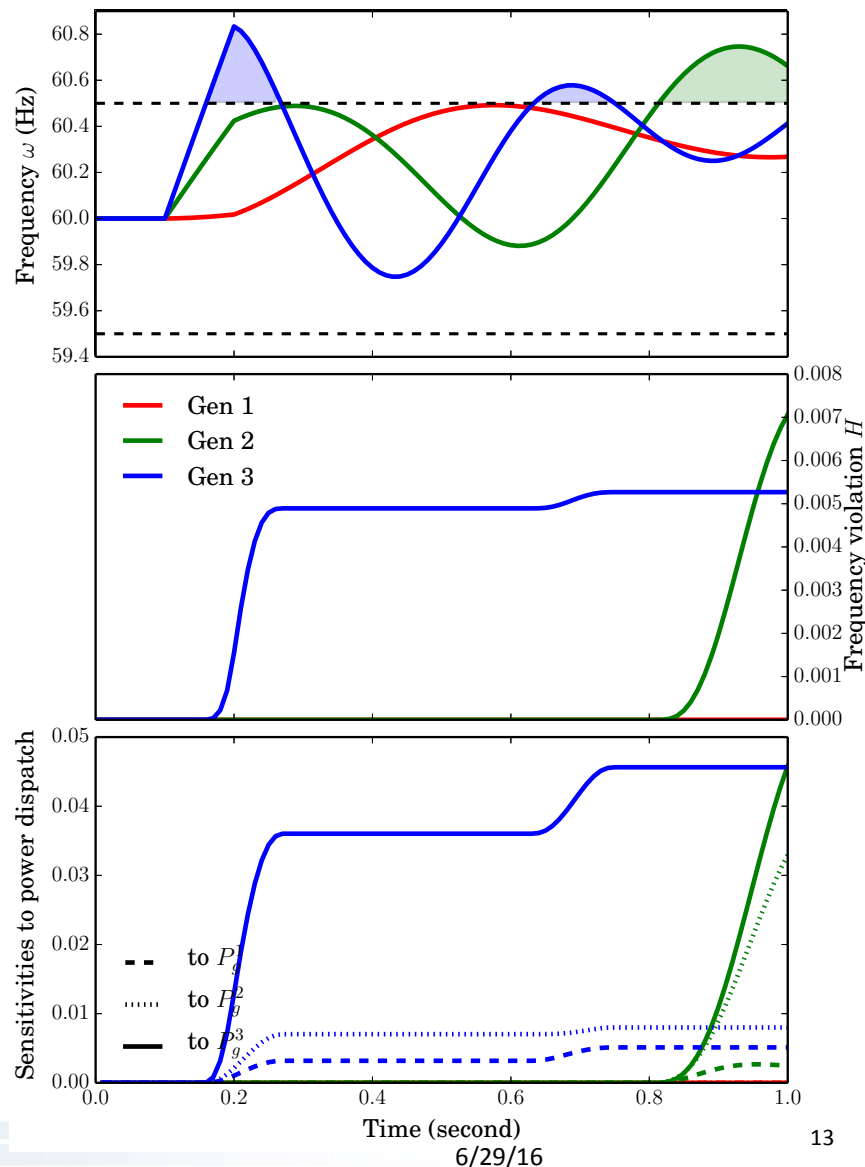
- $\omega_i$ : the frequency of the generator  $i$
- $\omega^+/\omega^-$ : the max and min freq limits

- Compute sensitivity of each  $H_i$  w.r.t. generator active and reactive dispatch, and the bus voltage magnitudes and angles at initial time

	No. of Variables	No. of Parameters	No. of Functions
9 bus	42	24	3
118 bus	884	344	54

	Forward	Adjoint	Simulation
9 bus	0.12 s	0.05 s	0.03 s
118 bus	14.00 s	1.82 s	0.33 s

The adjoint method is faster than the forward method by 2.4X and 7.7X for the 9-bus and 118- bus systems



# Bayesian Approach for Parameter Estimation

- Estimate generator inertias during dynamic transient generated by inducing a load disturbance

$$d = H(\mathcal{N}(p)) + \varepsilon, \quad \varepsilon \sim \mathcal{N}(0, \Gamma_{\text{noise}})$$

- Measurements: voltage phase and amplitude

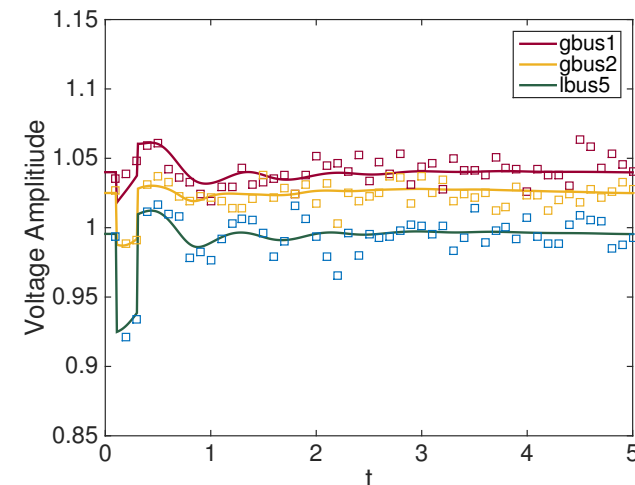
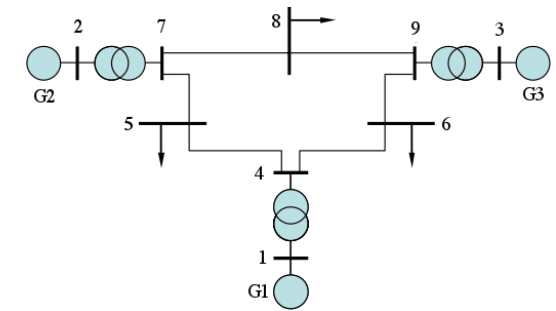
$$\pi_{\text{like}}(d|p) = \exp\left(-\frac{1}{2} (H(\mathcal{N}(p)) - d)^T \Gamma_{\text{noise}}^{-1} (H(\mathcal{N}(p)) - d)\right)$$

$$\log \pi_{\text{post}}(p) \propto -\|H(\mathcal{N}(p)) - d\|_{\Gamma_{\text{noise}}^{-1}} - \|p - p_{\text{prior}}\|_{\Gamma_{\text{prior}}^{-1}}$$

- Need to maximize the maximum a posteriori estimate:

$$p_{\text{MAP}} = \arg \max_p - \log(\pi_{\text{post}}(p))$$

Noemi Petra, Cosmin G. Petra, Zheng Zhang, Emil M. Constantinescu, and Mihai Anitescu, "A Bayesian approach for parameter estimation with uncertainty for dynamic power systems." *IEEE Transactions on Power Systems*, Submitted, 2016.



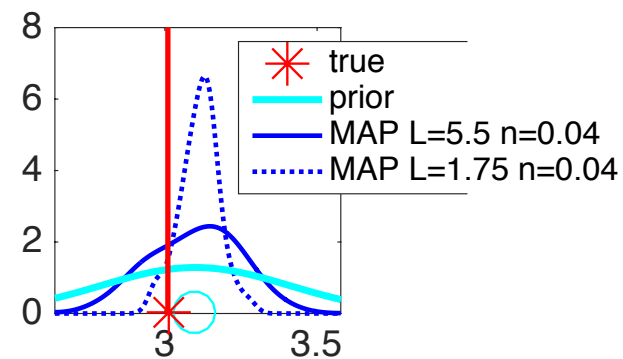
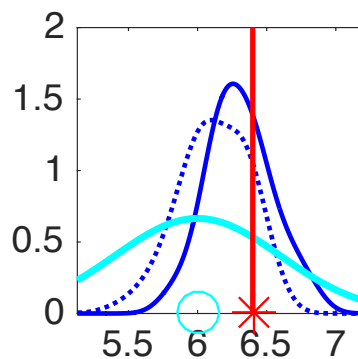
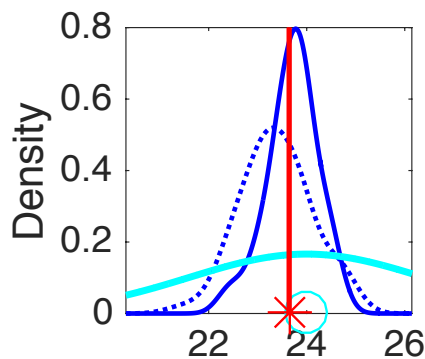
# Bayesian Approach for Parameter Estimation

- Use adjoints to compute the gradient of the posterior distribution
- The optimization is solved with quasi-Newton in TAO/PETSc

$$p_{\text{MAP}} = \arg \max_p - \log(\pi_{\text{post}}(p))$$

$$\mathcal{S} = - \frac{\partial \log(\pi_{\text{post}})}{\partial p}$$

$t_f$	$m_1$ <b>23.64</b>	$m_2$ <b>6.40</b>	$m_3$ <b>3.01</b>	#iter	$\tau$
(a) $\Delta_t = 0.01, \Delta_t^{obs} = 0.05$					
5.0	23.60	6.35	3.02	15	1.59e-02
3.0	23.79	6.39	3.06	9	1.85e-02
1.0	23.56	6.32	3.06	14	3.60e-02
0.8	23.67	6.54	2.95	11	5.81e-02
0.6	22.45	6.14	3.01	10	9.43e-02



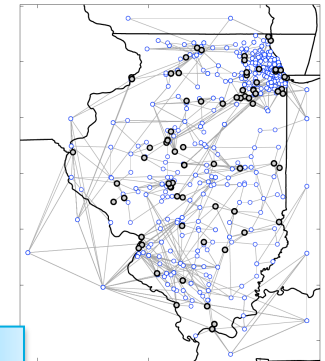
Noemi Petra, Cosmin G. Petra, Zheng Zhang, Emil M. Constantinescu, and Mihai Anitescu, "A Bayesian approach for parameter estimation with uncertainty for dynamic power systems." *IEEE Transactions on Power Systems*, Review, 2016.

# Adjoint Sensitivity Analysis for Targeted Generation Cost

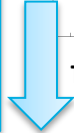
- Sensitivity of [energy generation] cost functional with respect to ambient conditions:

$$G(w(t)) [\text{\$}] = c(t) + \lambda(t)^T \omega(w(t)) \longrightarrow \mathcal{S} = \frac{\partial G}{\partial \mathbf{W}(t)}$$

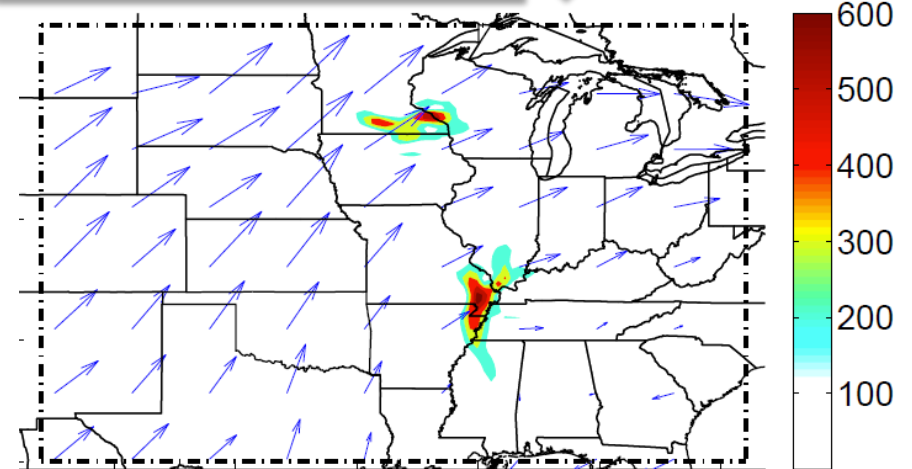
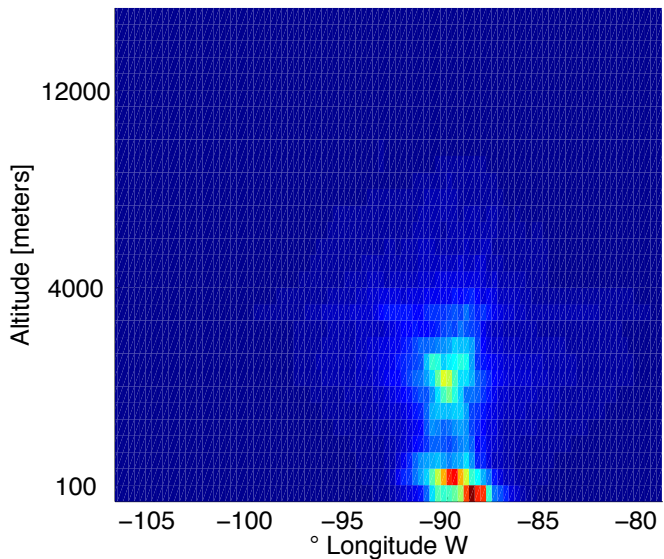
- Applications: sensor placement, reduce uncertainty with detailed simulation, reveals correlations among physical variables and economic functions



Sensitivity of grid operation costs with respect to weather conditions



target: cost in IL



Alexandru Cioaca, Victor Zavala, and Emil M. Constantinescu, "Adjoint Sensitivity Analysis for Numerical Weather Prediction: Applications to Power Grid Optimization." *Networking and Analytics for the Power Grid*, 2011.

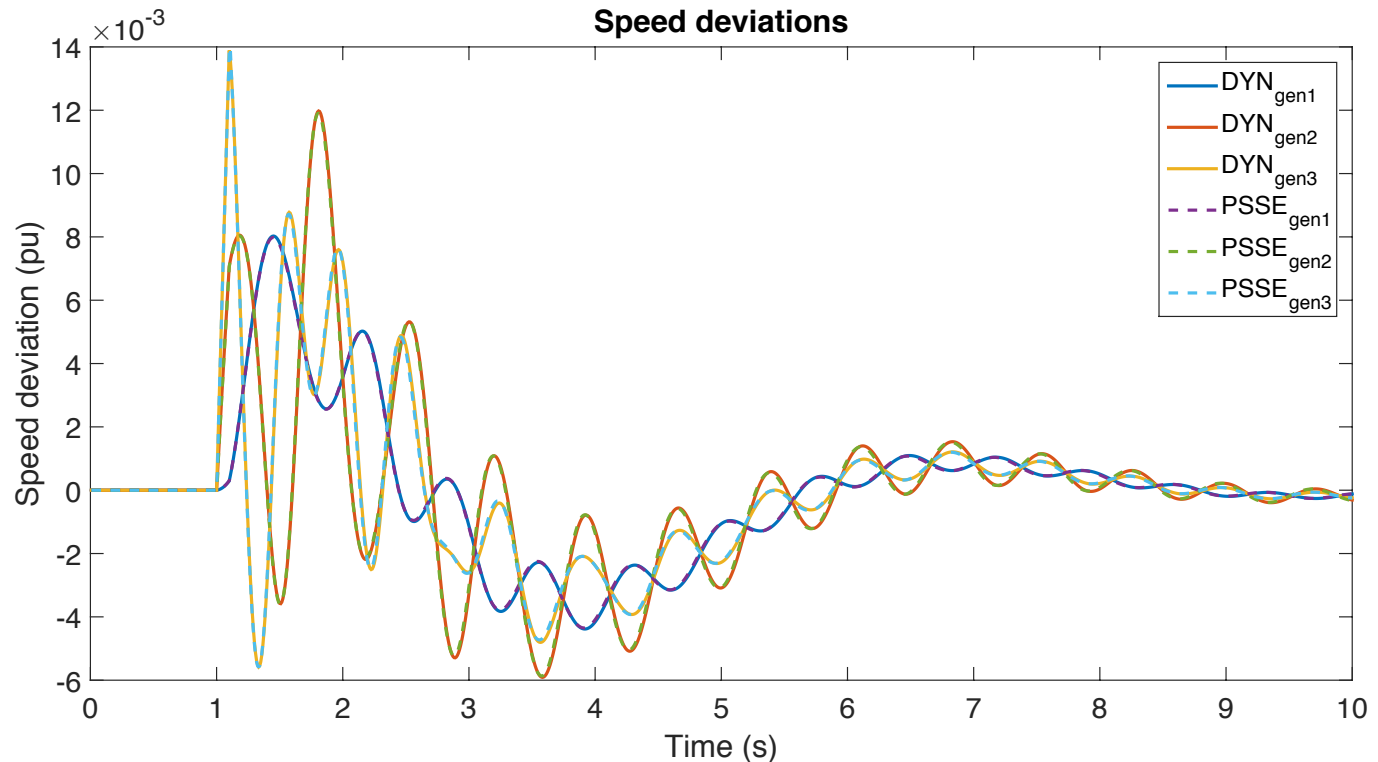
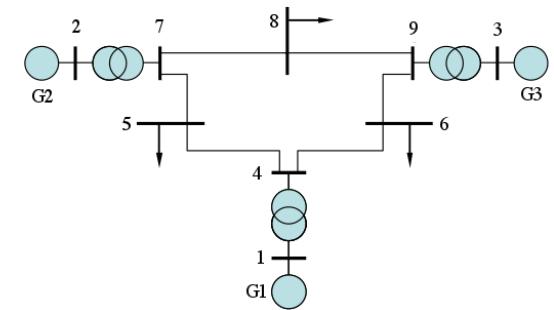




# Dynamic Code Consistency (vs PSSE)

Transient stability analysis: IEEE 9bus, fault for 0.1 sec

1. Generators: GENROU
2. Exciters: IEET1
3. Governors: TGOV1
4. Stabilizers: STAB1

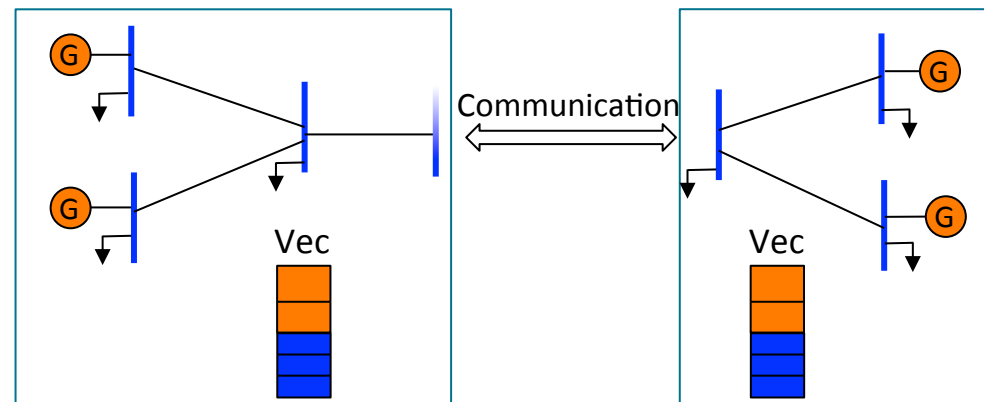


# Large Scale Dynamic Simulations Using PETSc

- Dynamic power grid simulation: 10 second-simulation with a six cycle temporary three-phase fault applied at a bus for 1 second
- 16-core machine, peak speedups of about 3 or 4

CaseName	Buses	Generators	Branches	Test System	PETSc
case2737sop	2737	399	3506	case2737sop	23.58
case9241pegase	9241	1445	16049	9241pegase	90.79
case22996	22996	2416	27408	case22996	138.02

- Parallel direct solvers are not scalable: use MUMPS and SuperLU\_Dist
- Preconditioned GMRES more scalable: use additive Schwarz
- Adaptive time stepping



*Shrirang Abhyankar, Emil M. Constantinescu, Barry Smith, Alexander J. Flueck, and Daniel A. Maldonado "Acceleration of dynamic simulations using parallel Newton-GMRES-Schwarz methods." IEEE Transactions on Smart Grid Special Issue on High Performance Computing (HPC) Applications for a More Resilient and Efficient Power Grid, Under Review, 2015.*

# Summary

- Local sensitivity analysis using discrete adjoints
- Most efficient and accurate for problems with many decision parameters
- The implementation takes advantage of highly developed solver infrastructure: MPI, parallel vectors/matrices, domain decomposition, linear/nonlinear solvers
- Advanced checkpointing, transparent to the user
- Current implementation avoids complete algorithmic differentiation and requires minimal user input, reuses information provided for the forward simulation
- Implementation accommodates jumps/switches/discontinuities
- Experiments on parameter estimation, dynamic security constraints for IEEE 9-bus and 118-bus dispatch parameters; and other large scale problems

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