New Tools for Analysing Power System Dynamics

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(With support from many talented people.)

PSerc Research Tele-Seminar
March 2, 2004

Two main themes

Dealing with parameter uncertainty

- How much confidence is there in load model parameters? Generator parameters?
- Simulation is too time-consuming to repeat studies for multiple parameter sets.

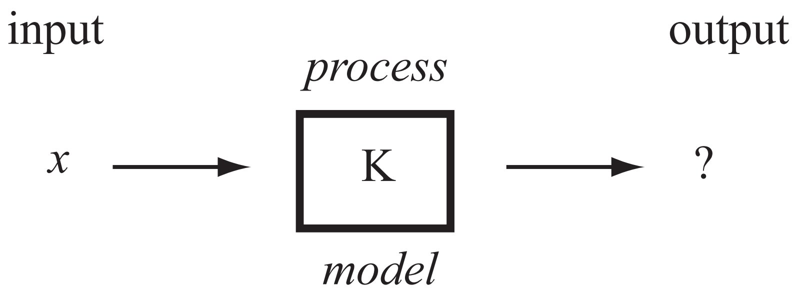
Inverse problems

- What does this mean?

Trajectory sensitivities form a common link between these two areas.

Inverse problems

Direct problem:



input

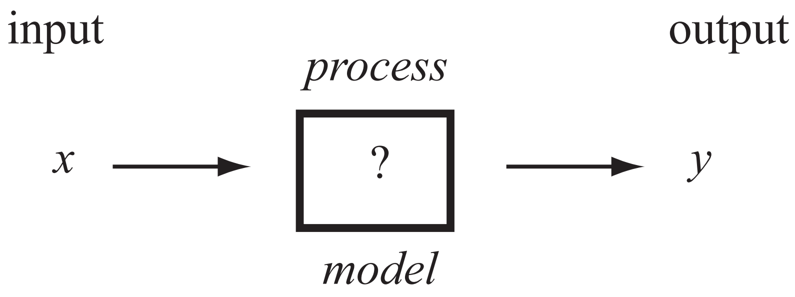
process

output

$x \longrightarrow \boxed{K} \longrightarrow ?$

model

Inverse problem (system identification):



input

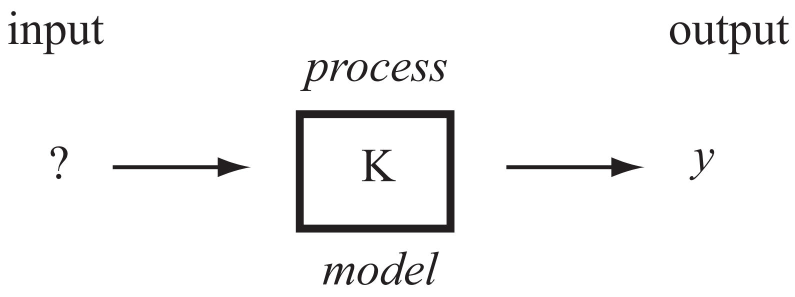
process

output

$x \longrightarrow \boxed{?} \longrightarrow y$

model

Inverse problem (causation):



input

process

output

$? \longrightarrow \boxed{K} \longrightarrow y$

model

Inverse problems (continued)

Power system context

- Identification problems
    - ∗ Load models and parameters
    - ∗ Generator parameters
- What controller parameters ensure appropriate fault-recovery dynamics?
- What load changes maintain dynamic security?
- Under what conditions could a fault induce incidental protection operation?
    - ∗ Protection operation caused by post-fault transients.

Trajectory sensitivities

Let $\phi(t;\lambda)$ describe the trajectory (flow), at time t, due to parameters λ.

- Determined by simulation.

The corresponding trajectory sensitivities are $\Phi(t;\lambda) \equiv \frac{\partial\phi}{\partial\lambda}(t;\lambda)$.

Characteristics of sensitivities Φ:

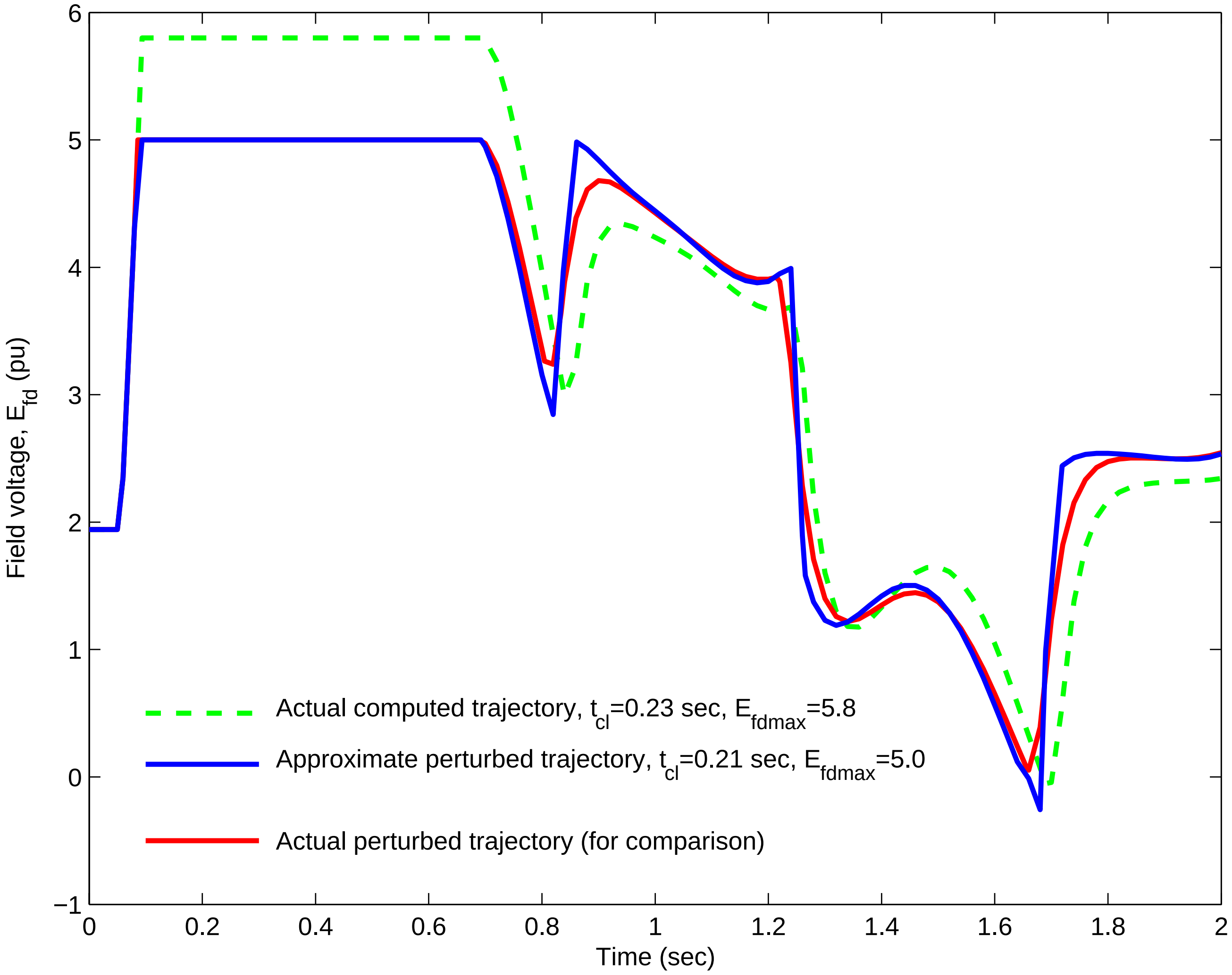
- Quantify the change in a trajectory due to a small change in parameters.
- Can be computed efficiently, as a by-product of simulating the nominal trajectory.
- Well defined for nonlinear non-smooth systems.
- Provide gradient information that underlies Newton-type algorithms (shooting methods).

Trajectory approximation

Taylor series expansion of the flow gives,

$$\phi(t;\lambda+\Delta\lambda)=\phi(t;\lambda)+\Phi(t;\lambda)\Delta\lambda$$

Example:
Generator field
voltage.

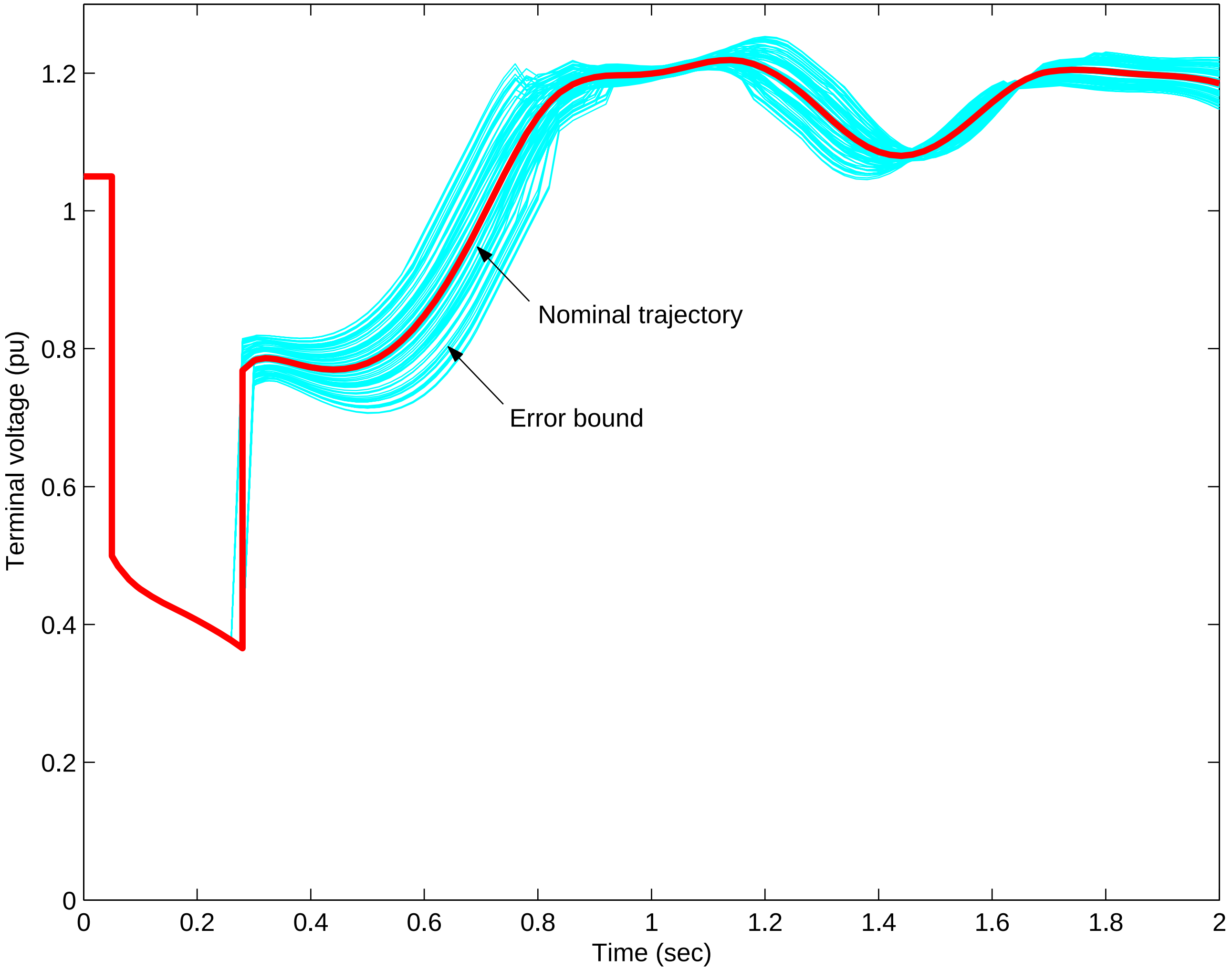


Error bounds

Many system parameters are not known precisely, but are better described by probability distributions.

Select parameter sets using a Monte-Carlo process.

Form an approximate trajectory for each set.



Parameter estimation

Desire a systematic approach to:

- Determine which parameters are *well conditioned* (identifiable).
- Estimate those parameters

Algorithm: Minimize the nonlinear least-squares cost

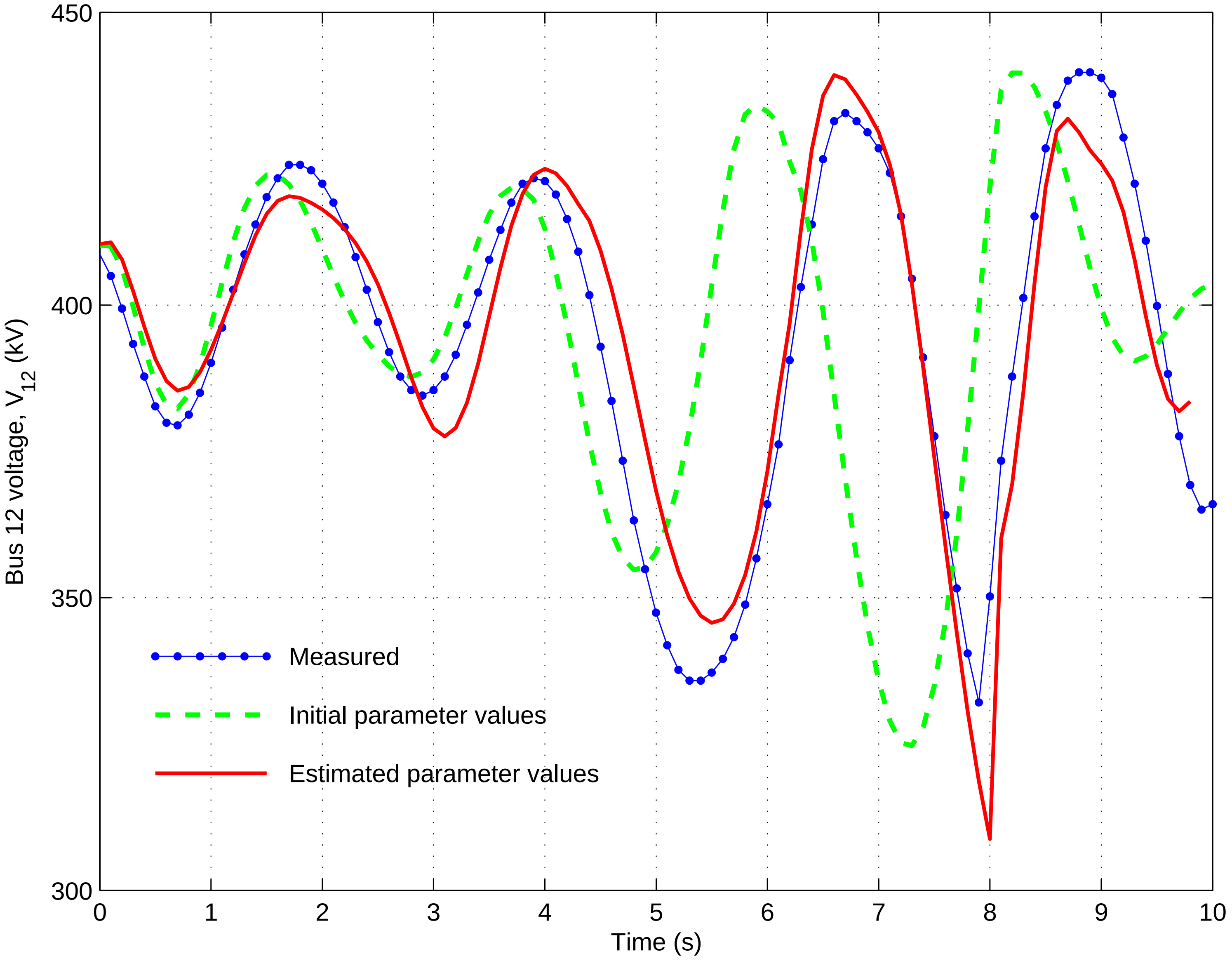
$$\mathcal{J}(\lambda) = \frac{1}{2}\sum_{k=1}^{m}\Big(\phi(t_k;\lambda) - ms(t_k)\Big)^2$$

via the Gauss-Newton iterative scheme

$$\begin{aligned} \underline{\Phi}(\lambda^j)^T\underline{\Phi}(\lambda^j)\Delta\lambda^{j+1} &= \underline{\Phi}(\lambda^j)^T\left(\underline{\phi}(\lambda^j) - \underline{ms}\right) \\ \lambda^{j+1} &= \lambda^j - \alpha^{j+1}\Delta\lambda^{j+1} \end{aligned}$$

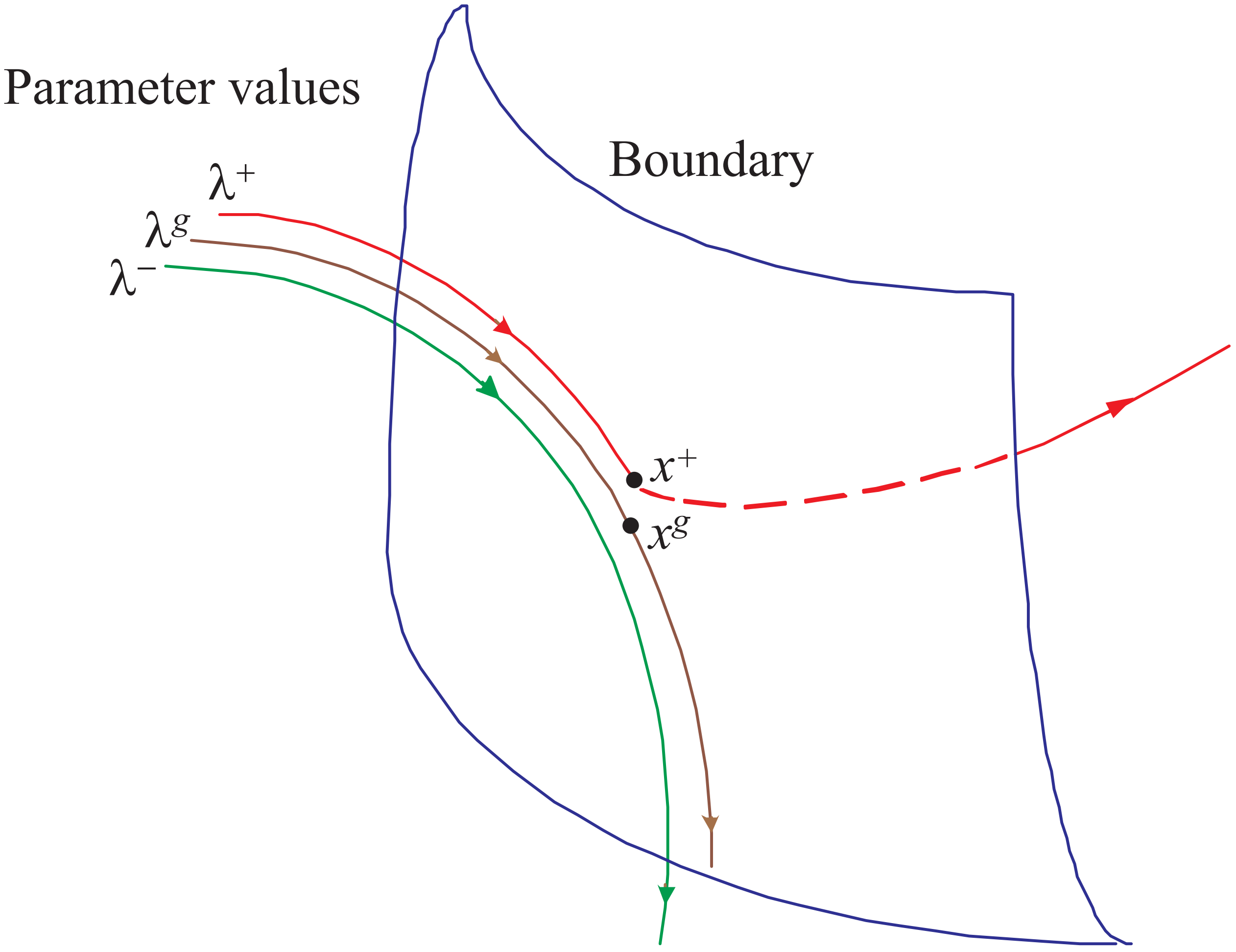
Parameter estimation (continued)

Nordel example



Performance specification (grazing)

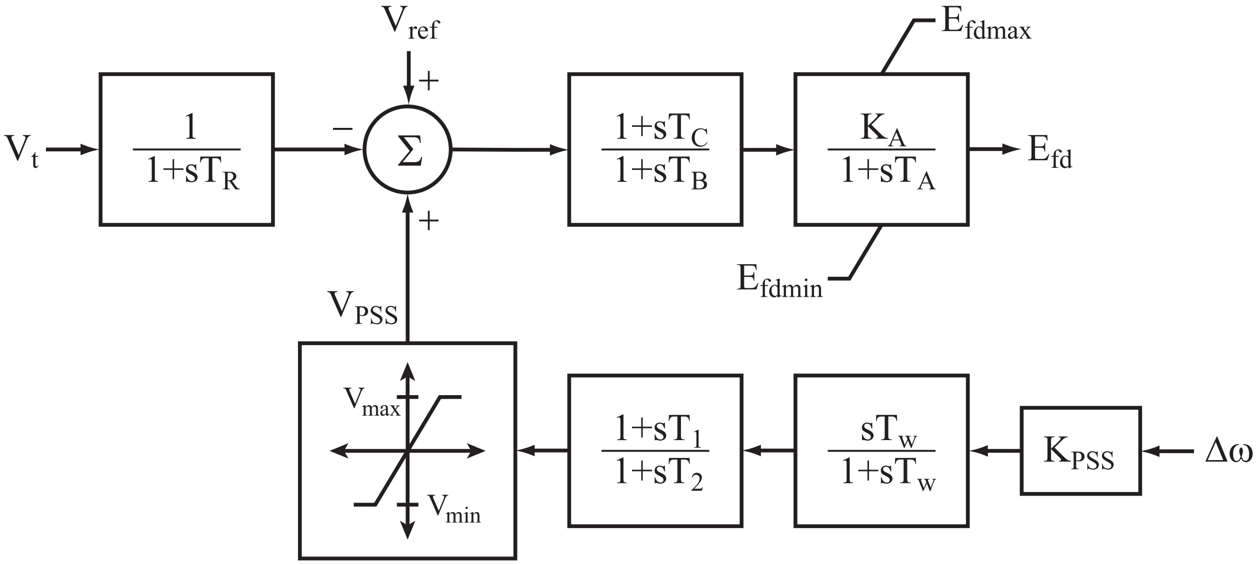
Trajectory is tangential to a performance boundary.



Performance specification (continued)

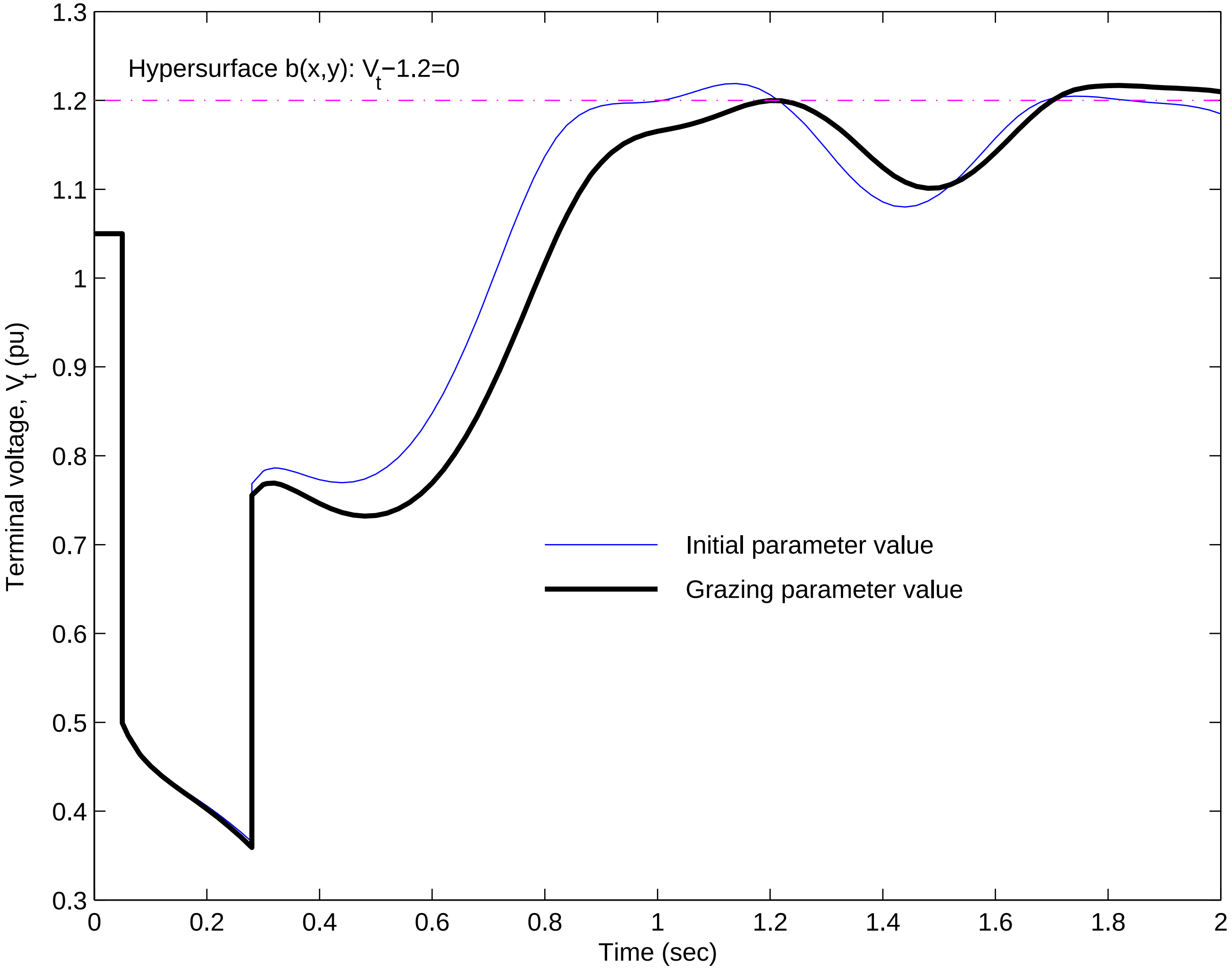
Example: Generator field control.

What value of $E_{fd,max}$ ensures voltage does not overshoot abnormally following a fault?



Performance specification (continued)

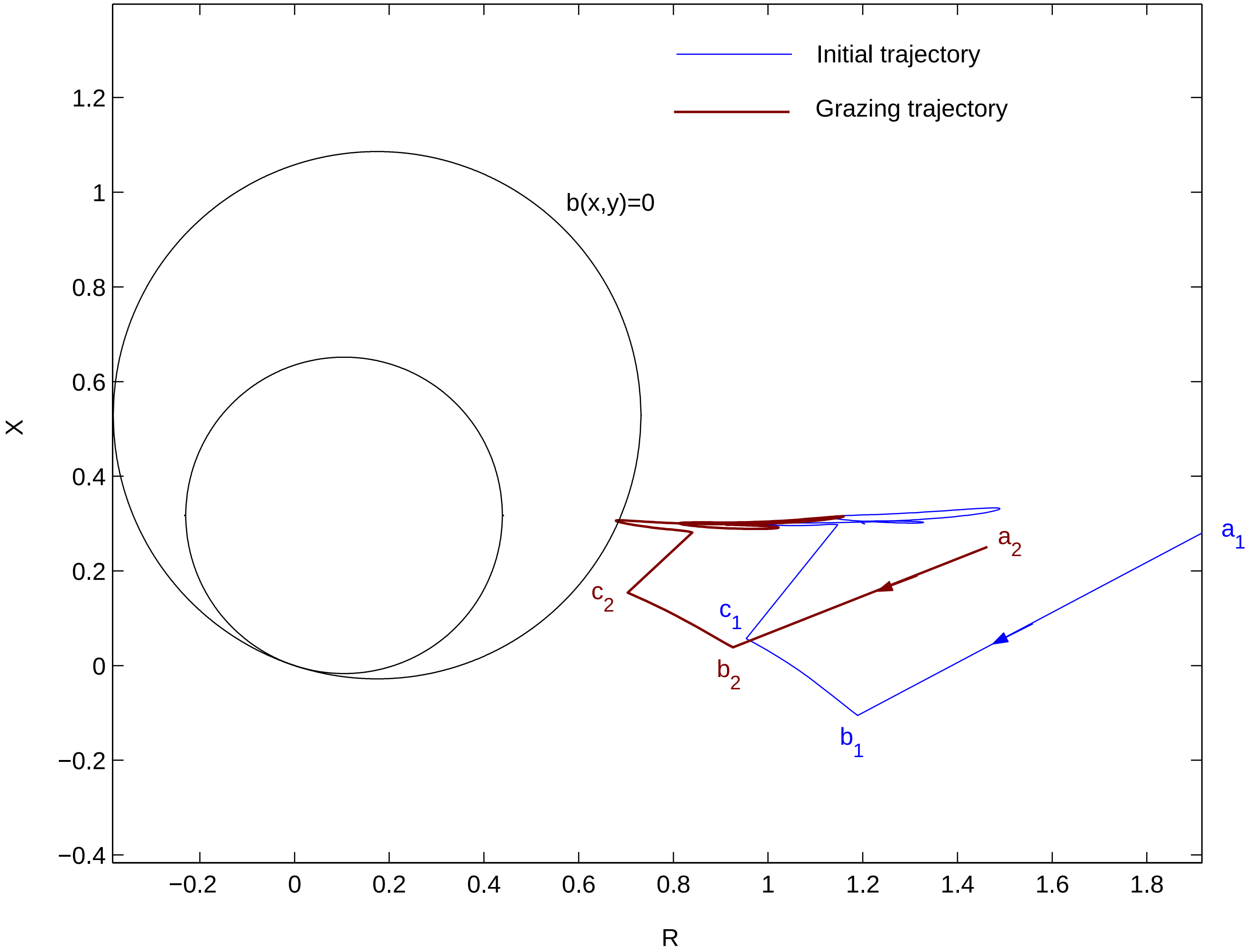
Terminal voltage constrained below 1.2 pu during initial transient.



Performance specification (continued)

Example: Distance protection.

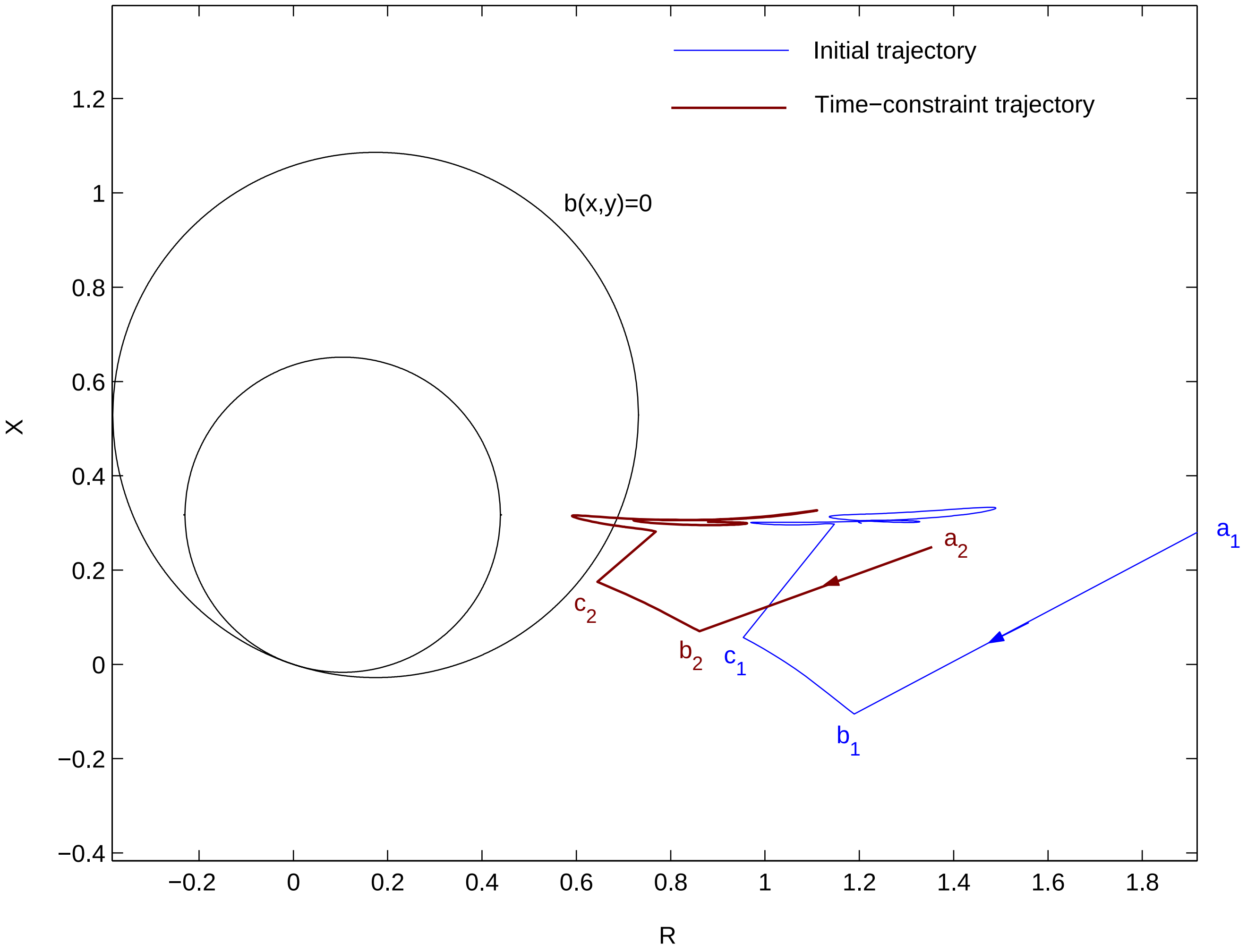
How far can load be increased before a fault disturbance induces incidental protection operation?



Performance specification (continued)

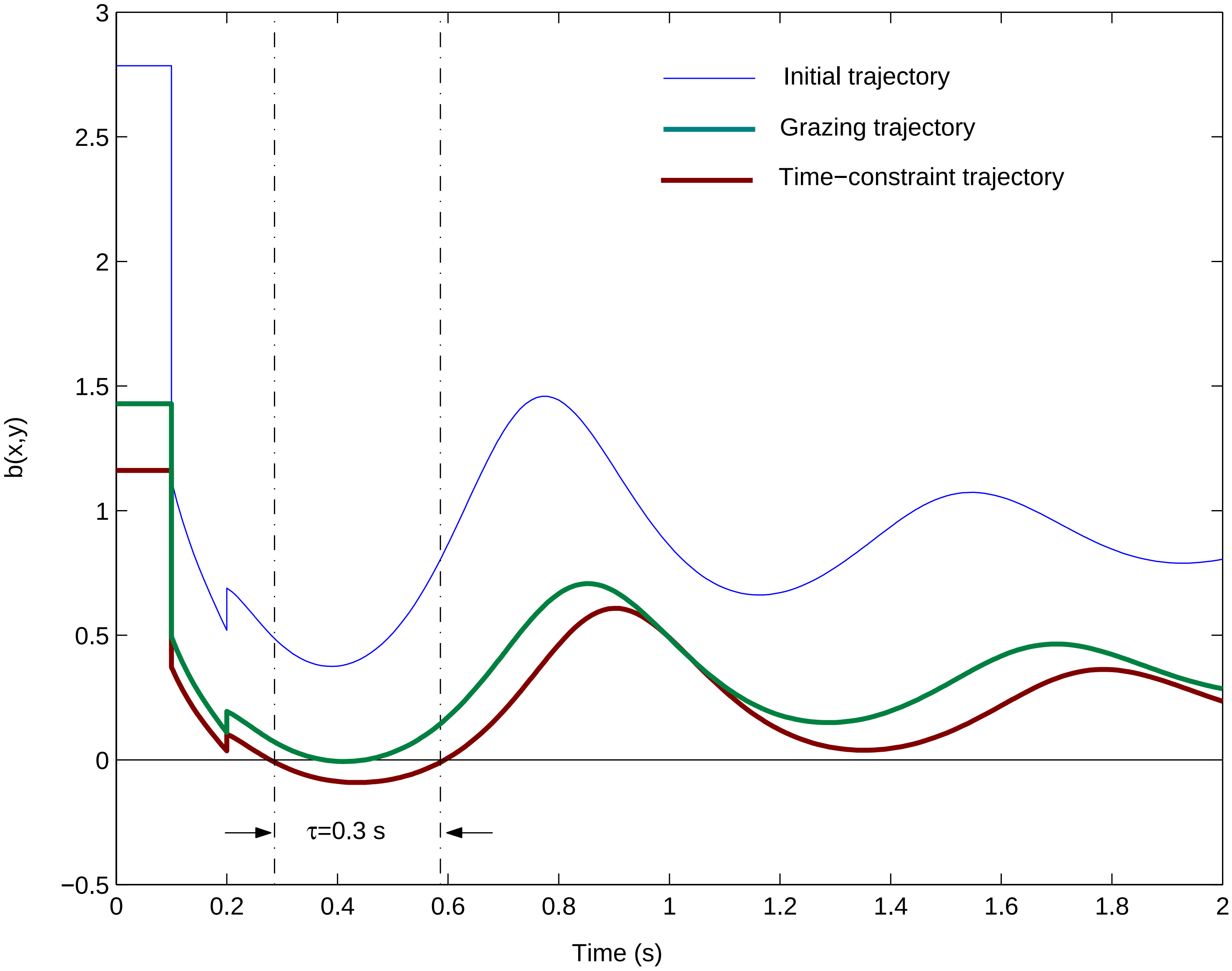
Example: Distance protection with timing.

Replace conditions enforcing tangential contact by conditions specifying time inside mho characteristic.



Performance specification (continued)

Initial, grazing, and time-constraint cases.



Dynamic embedded optimization

Minimize the cost

$$\mathcal{J}(\lambda) = \varphi\big(\phi(t_f;\lambda),\lambda,t_f\big) + \int_{t_0}^{t_f} \psi\big(\phi(t;\lambda),\lambda,t\big)dt$$

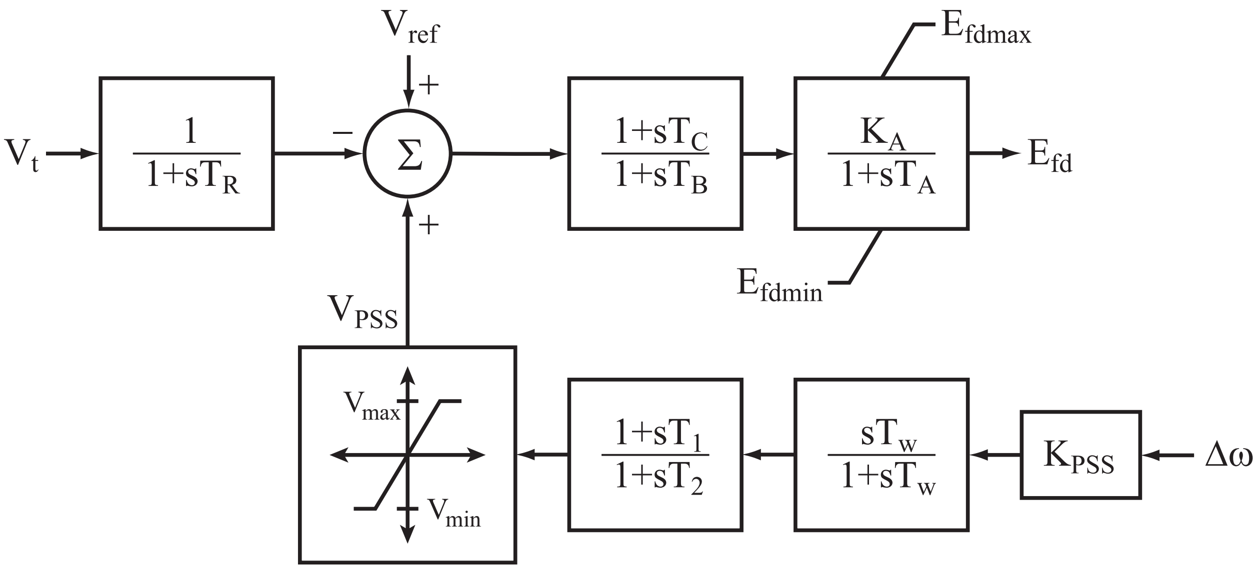
where $\phi(t;\lambda)$ satisfies the dynamic model.

- Closely related to optimal control, but optimizing over finite dimensional design parameters.
- Some technical issues arise for hybrid (switched) systems if event order changes.

Dynamic embedded optimization (continued)

Example: AVR/PSS tuning

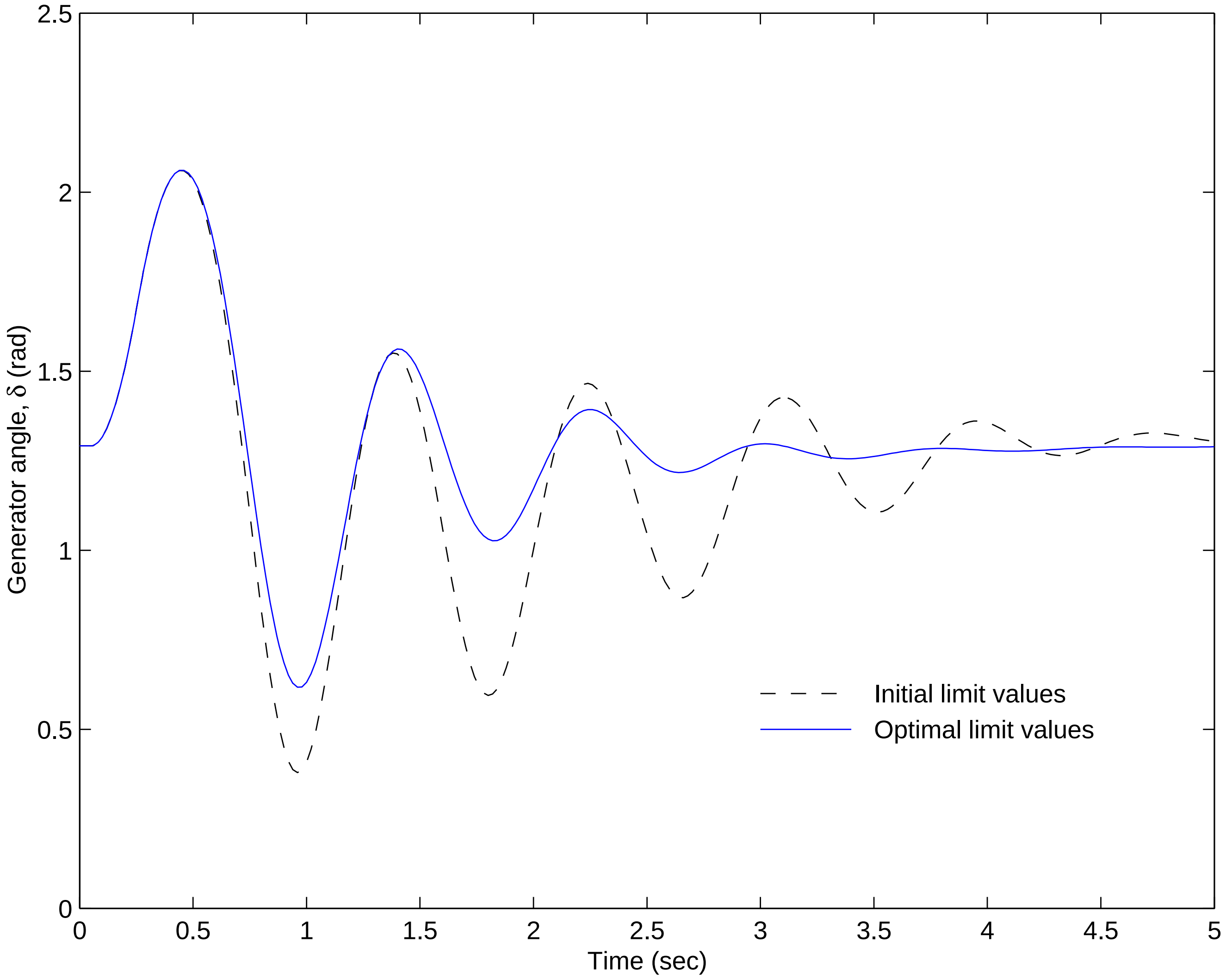
What values of PSS output limits give best damping?



Dynamic embedded optimization (continued)

Optimization adjusted the lower PSS limit from -0.1 to -0.33 pu.

- Noticable damping improvement.



Conclusions

Parameter uncertainty is unavoidable in power systems, and should be considered in decision making.

- This is computationally feasible using first-order approximations of trajectories.

Many analysis and design processes are effectively "inverse problems".

- Such problems can be solved using gradient-based iterative algorithms.

In both cases, efficient computation of trajectory sensitivities underlies practical algorithms.

Extra Material

Simulation model

Differential Algebraic Impulsive Switched (DAIS) model

$$\dot{x} = f(x,y) + \sum_{i=1}^{r} \delta(y_{r,i}) \Big(h_i(x,y) - x \Big) \qquad \left\{ \begin{array}{ll} \dot{x} = f(x,y) & \\ x^{+} = h_i(x^{-}, y^{-}), & y_{r,i} = 0 \end{array} \right.$$

$$0 = g(x,y) \equiv g^{(0)}(x,y) + \sum_{j=1}^{s} g^{(j)}(x,y)$$

where

$$g^{(j)}(x,y) = \left\{ \begin{array}{ll} g^{(j-)}(x,y) & y_{s,j} < 0 \\ g^{(j+)}(x,y) & y_{s,j} > 0 \end{array} \right. \qquad j = 1, \ldots, s$$

Trajectory sensitivity computation

Smooth sections of trajectories evolve according to

$$\begin{aligned}\dot{x} &= f(x, y)\\ 0 &= g(x, y)\end{aligned}$$

Differentiating with respect to x_0 gives

$$\begin{aligned}\dot{\Phi}_x &= \frac{\partial f}{\partial x}(t)\Phi_x + \frac{\partial f}{\partial y}(t)\Phi_y\\ 0 &= \frac{\partial g}{\partial x}(t)\Phi_x + \frac{\partial g}{\partial y}(t)\Phi_y\end{aligned}$$

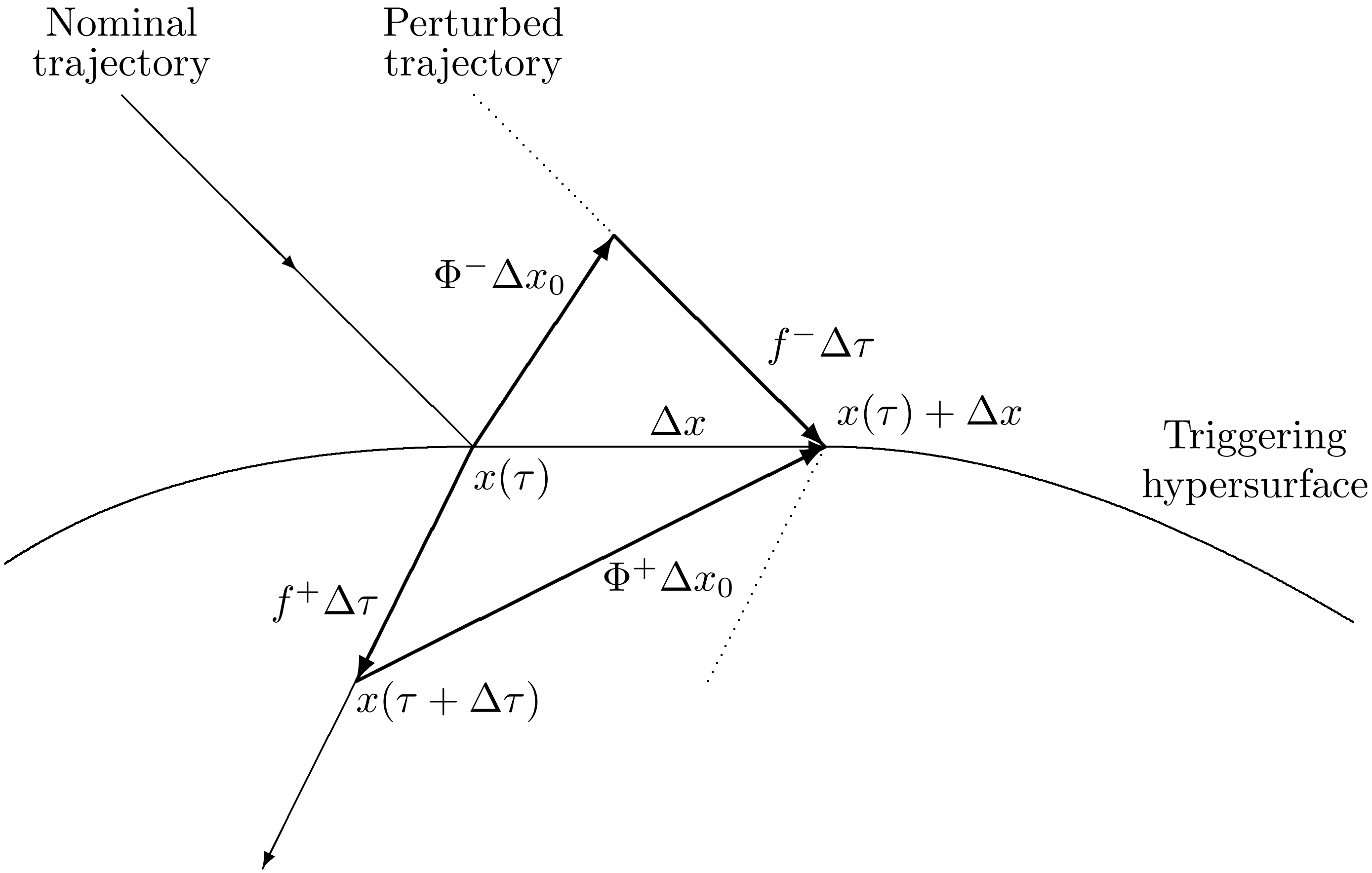
Initial conditions

$$\Phi_x(t_0) = I$$

Trajectory sensitivities at events

At an event (at time τ), sensitivities evolve according to jump conditions,

$$\Phi_x(\tau^+) = \Phi_x(\tau^-) - \left(f^+ - f^-\right)\frac{\partial \tau}{\partial x_0}$$



Grazing and time-constraint formulation

For simplicity, the ODE form of equations is presented rather than the DAE form.

Grazing

$$\begin{aligned}\phi(t_g;\lambda) - x_g &= 0\\ b(x_g) &= 0\\ b_x(x_g)f(x_g) &= 0\end{aligned}$$

Time constraint

$$\begin{aligned}\phi(t_1;\lambda) - x_1 &= 0\\ \phi(t_2;\lambda) - x_2 &= 0\\ b(x_1) &= 0\\ b(x_2) &= 0\\ t_1 - t_2 - \tau_{spec} &= 0\end{aligned}$$