

New Tools for Analysing Power System Dynamics

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(With support from many talented people.)

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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.

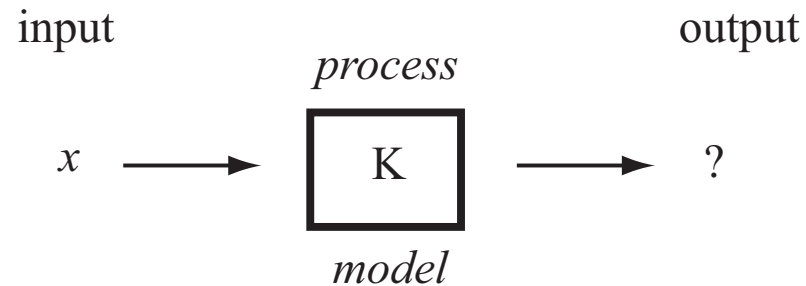
Inverse problems

- What does this mean?

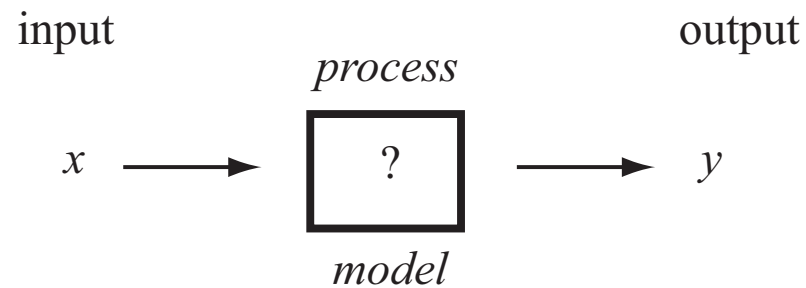
Trajectory sensitivities form a common link between these two areas.

Inverse problems

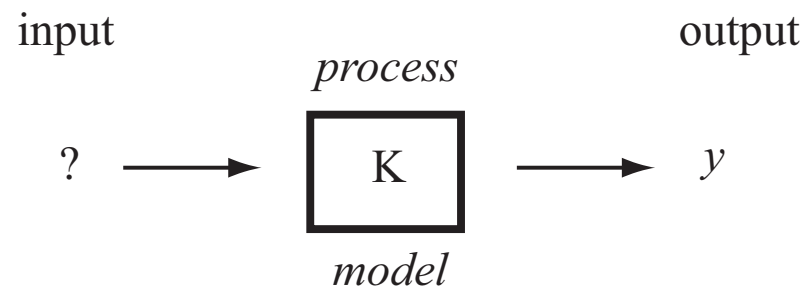
Direct problem:



Inverse problem (system identification):



Inverse problem (causation):



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 :

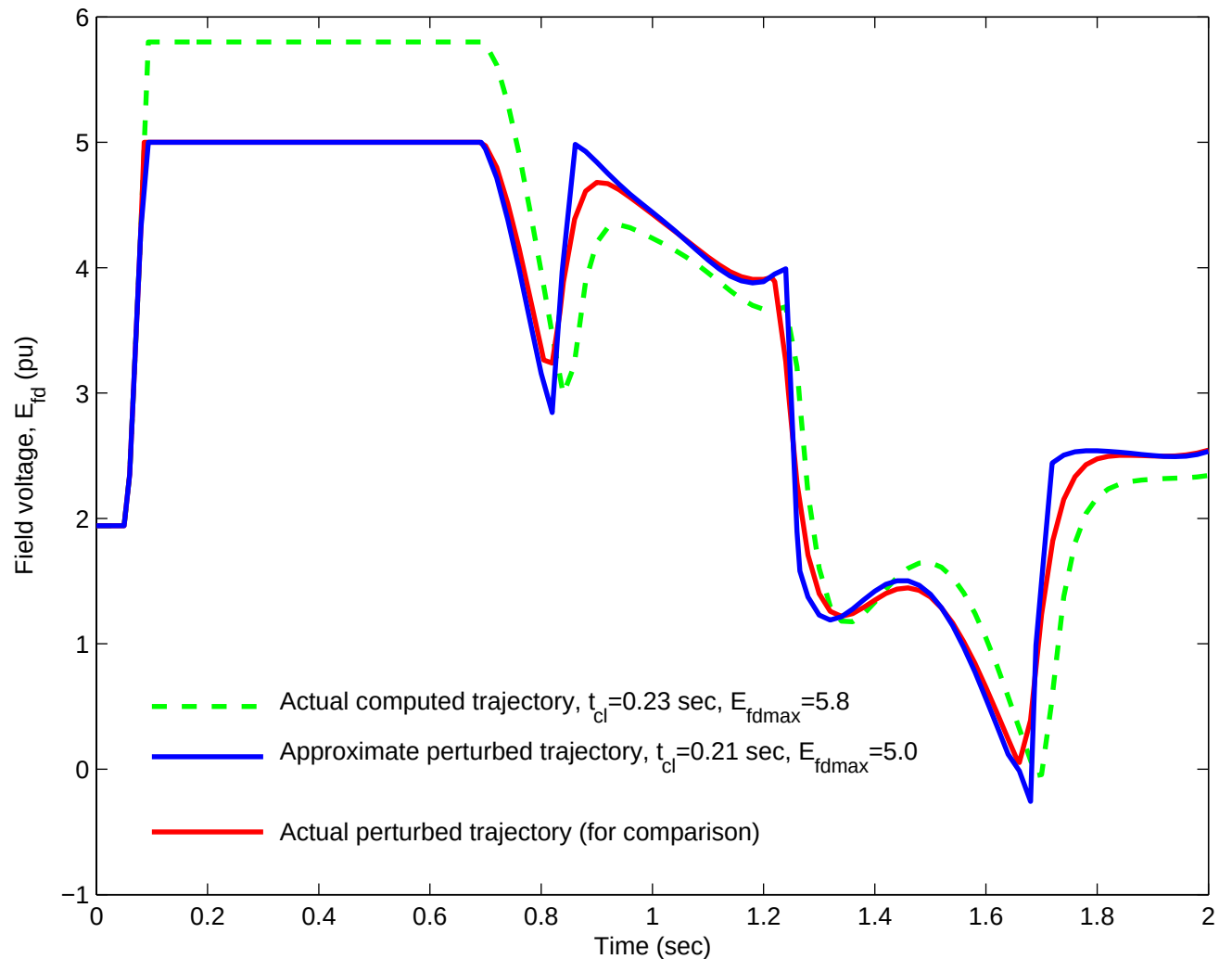
- Quantify the change in a trajectory due to a small change in parameters.
- Can be computed efficiently, as a by-product of simulating the nominal trajectory.
- Well defined for nonlinear non-smooth systems.
- Provide gradient information that underlies Newton-type algorithms (shooting methods).

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.

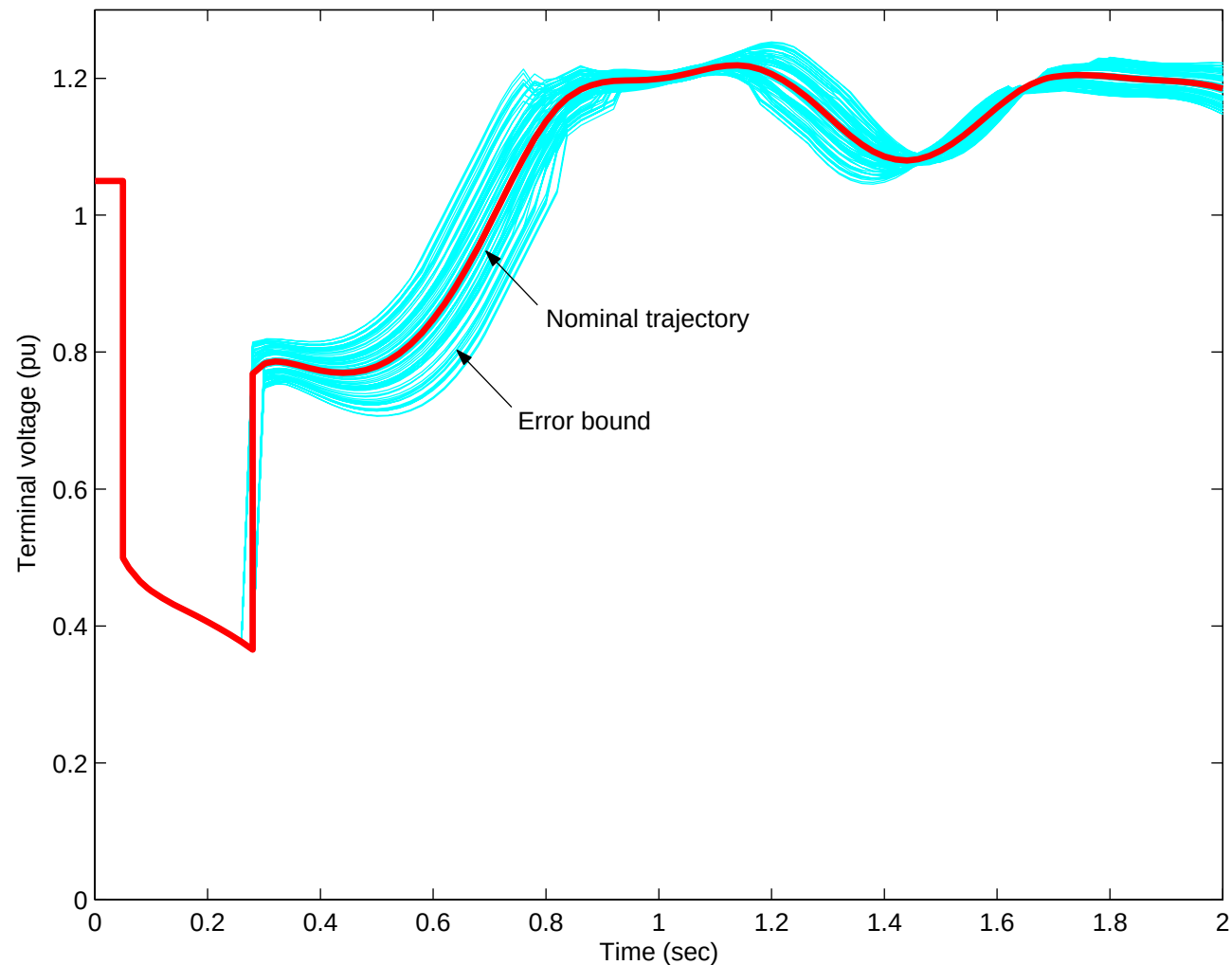


Error bounds

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

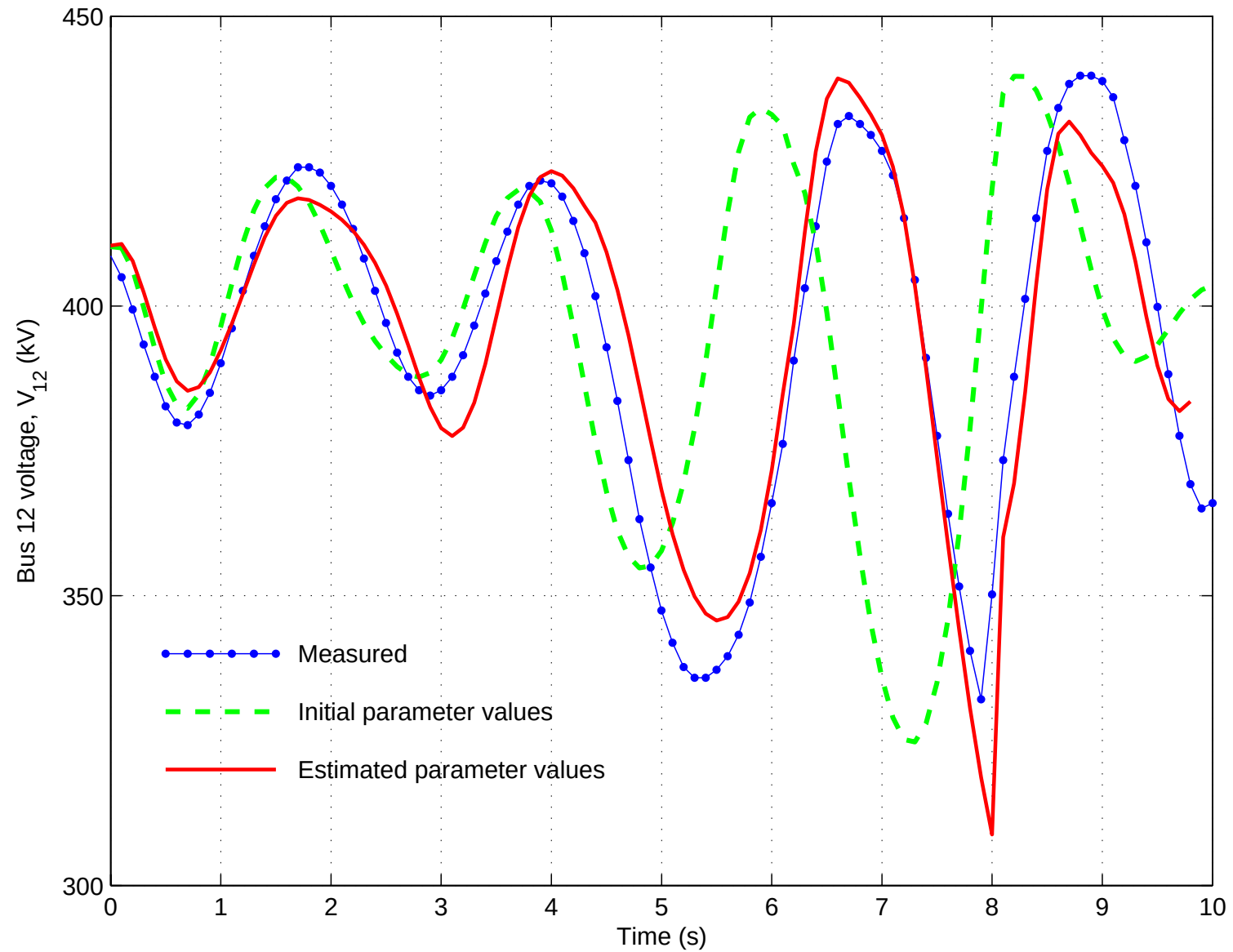
$$\mathcal{J}(\lambda) = \frac{1}{2} \sum_{k=1}^m \left(\phi(t_k; \lambda) - ms(t_k) \right)^2$$

via the Gauss-Newton iterative scheme

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

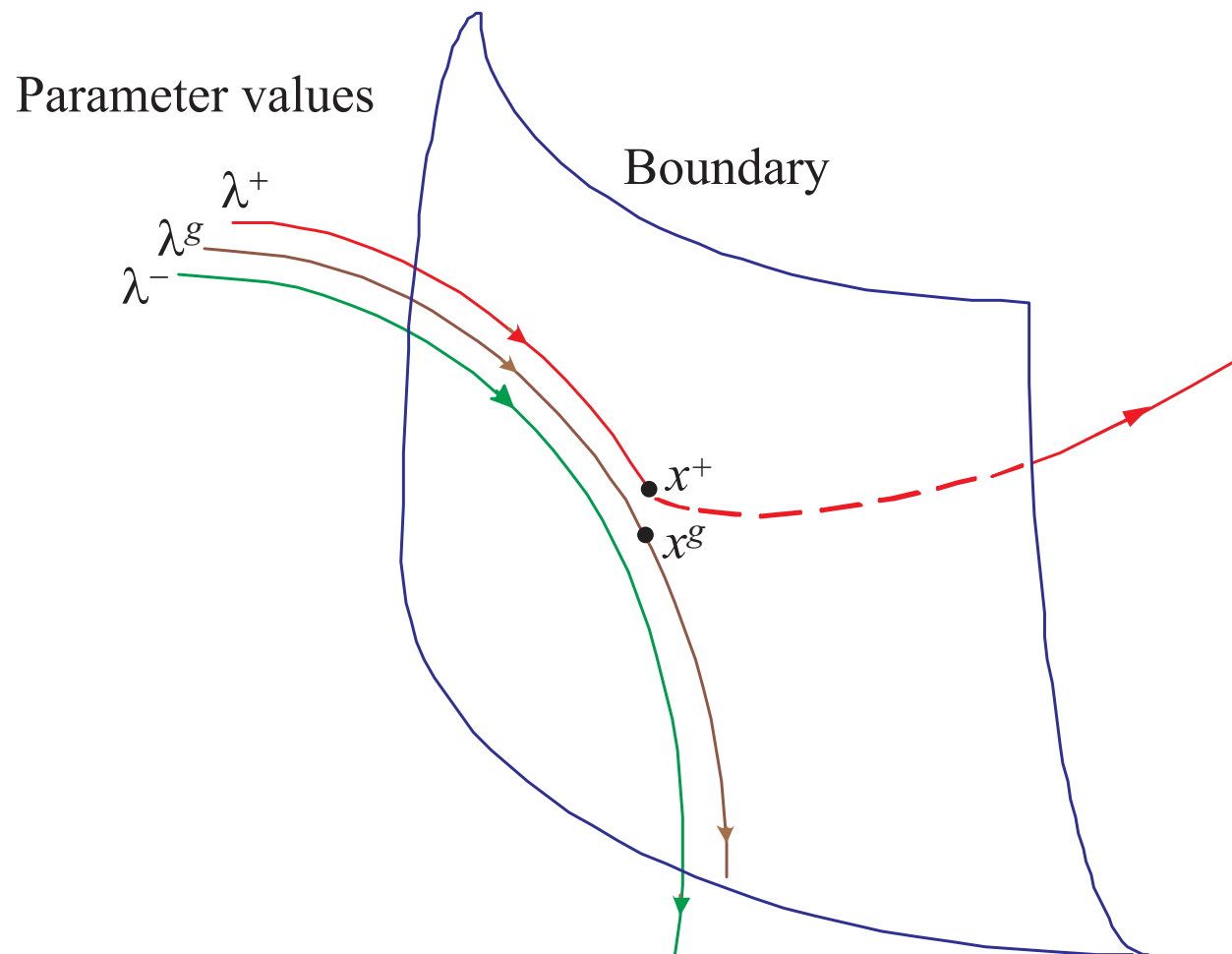
Parameter estimation (continued)

Nordel example



Performance specification (grazing)

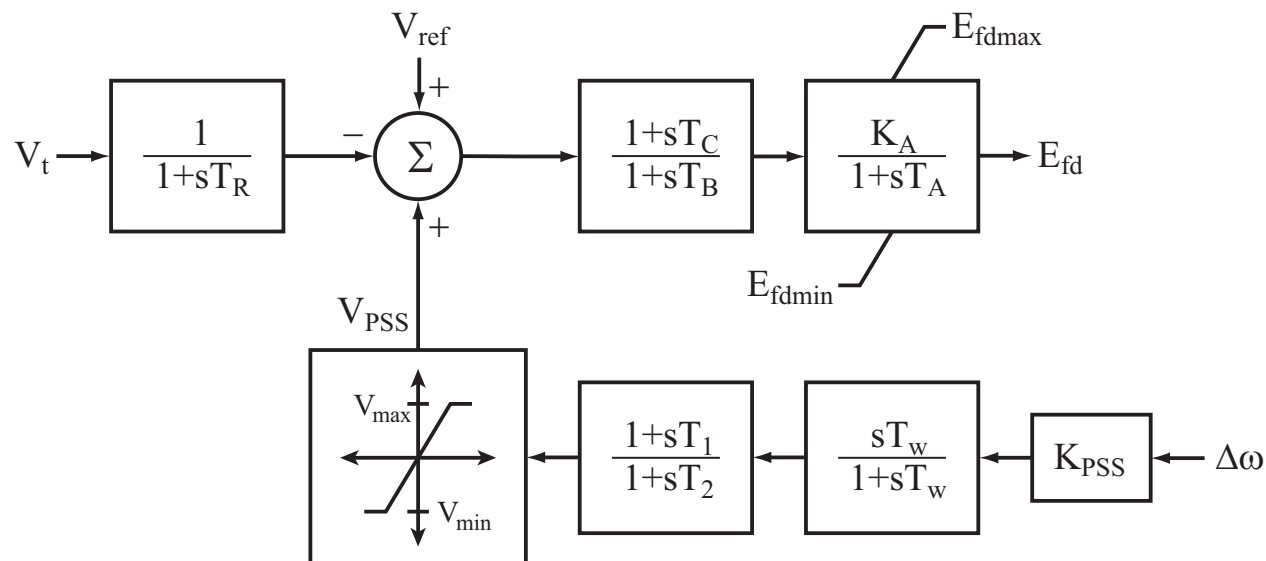
Trajectory is tangential to a performance boundary.



Performance specification (continued)

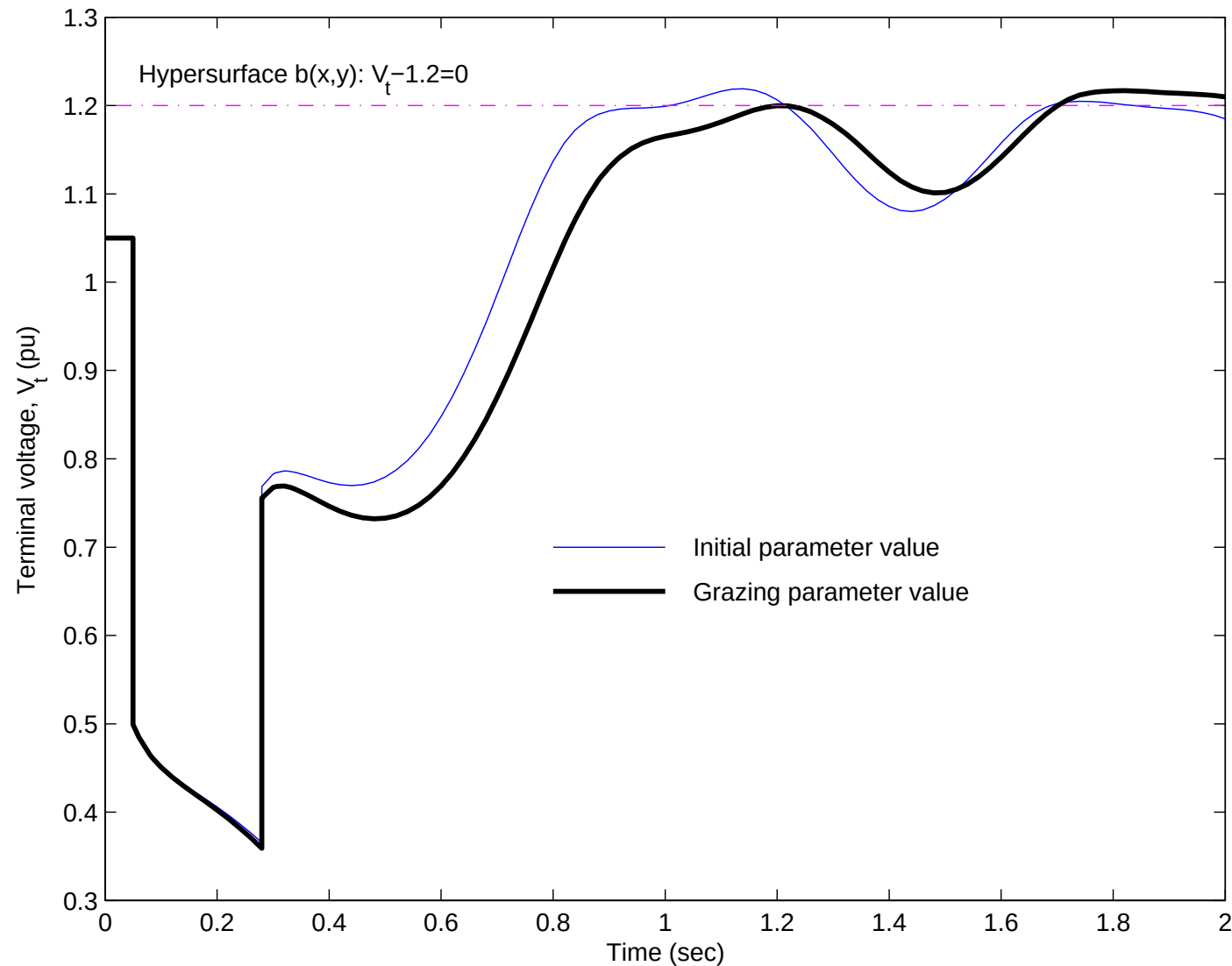
Example: Generator field control.

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



Performance specification (continued)

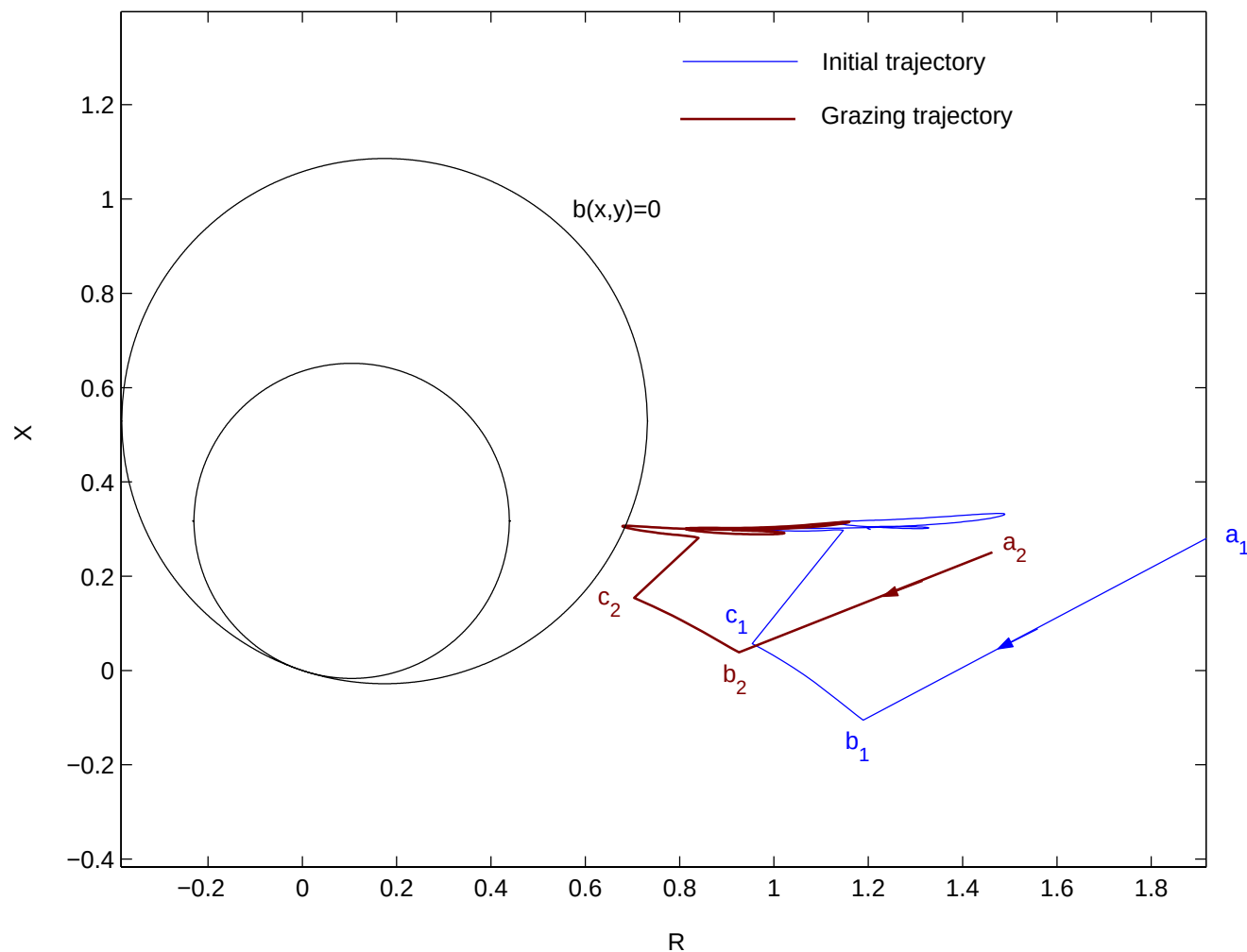
Terminal voltage constrained below 1.2 pu during initial transient.



Performance specification (continued)

Example: Distance protection.

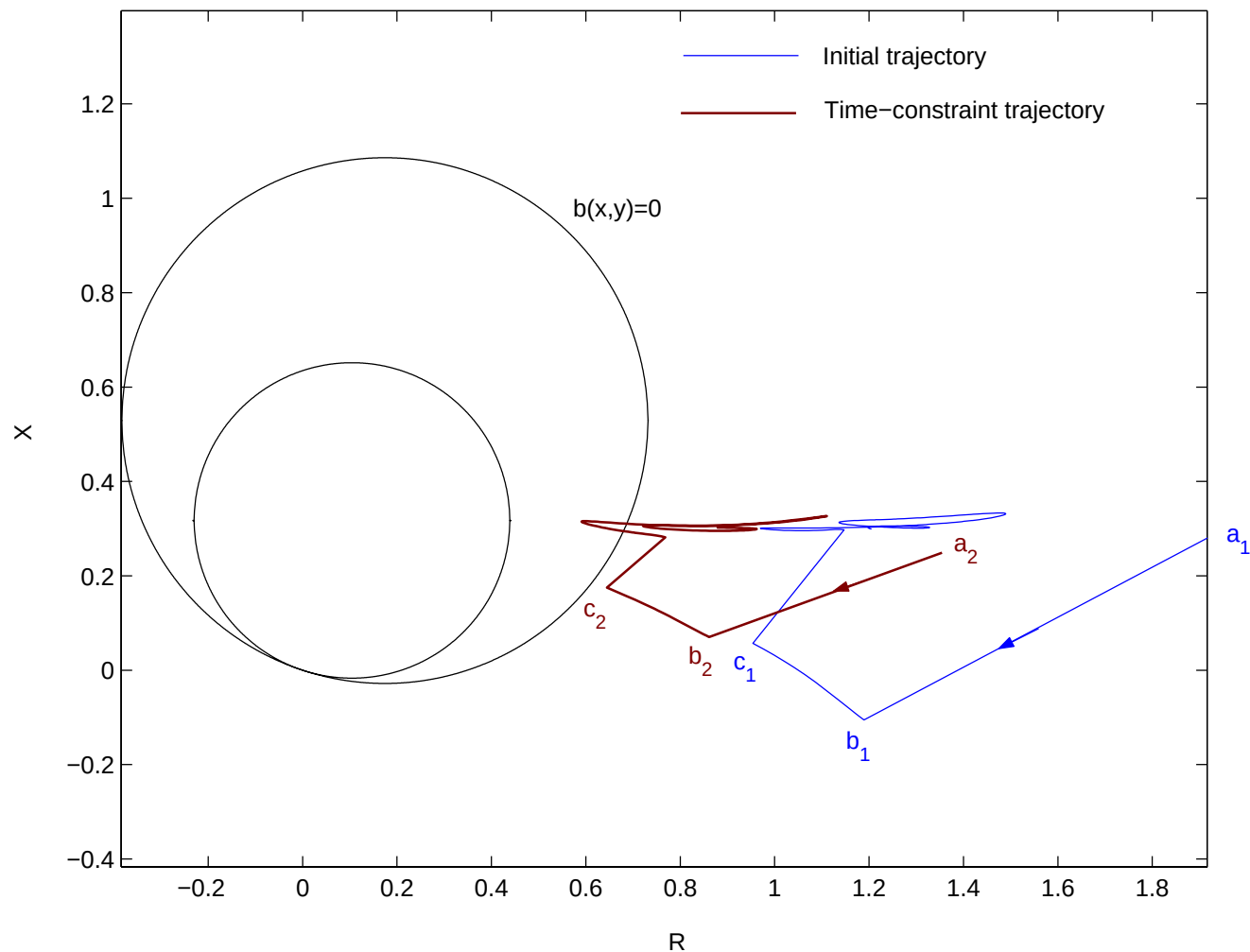
How far can load be increased before a fault disturbance induces incidental protection operation?



Performance specification (continued)

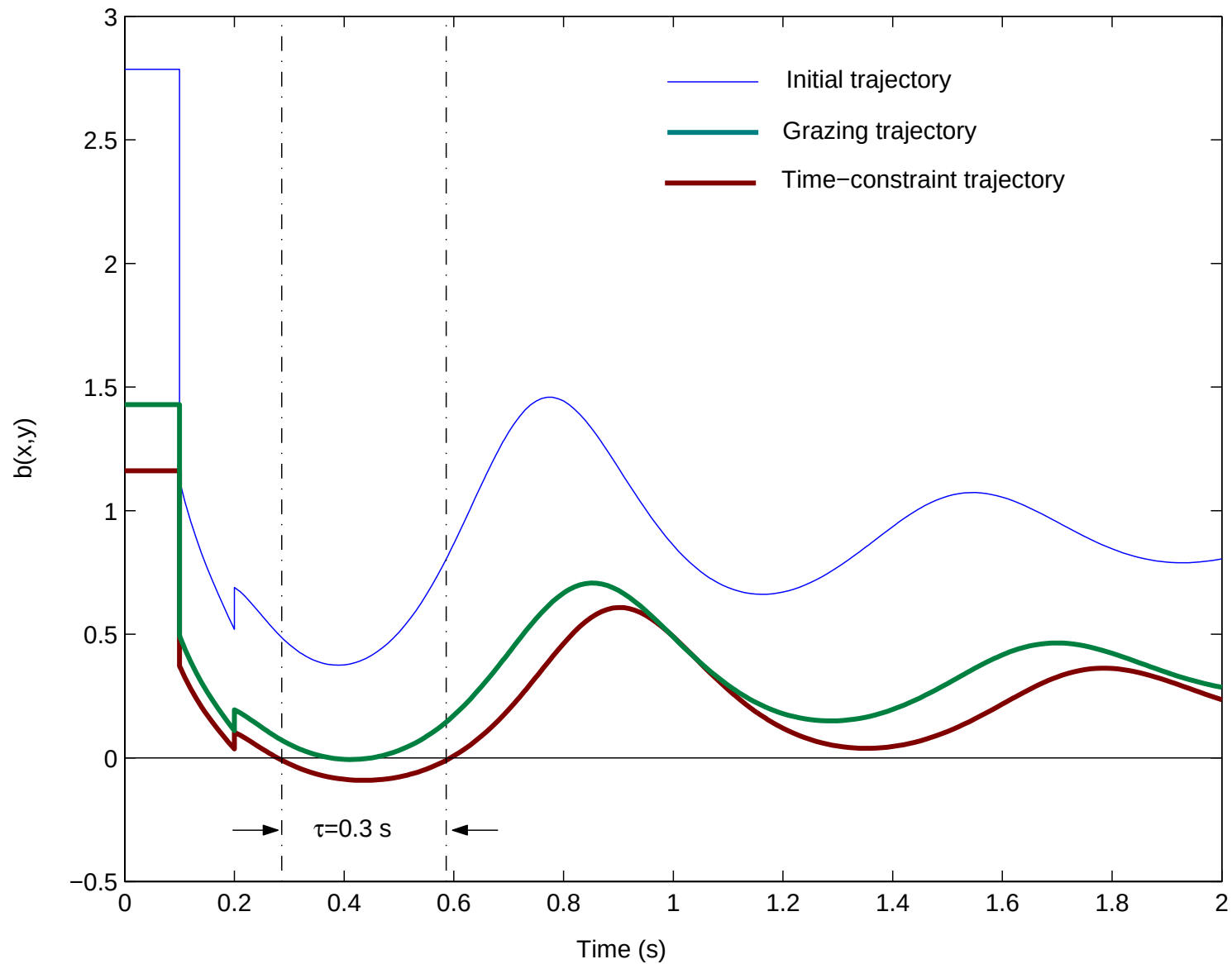
Example: Distance protection with timing.

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

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

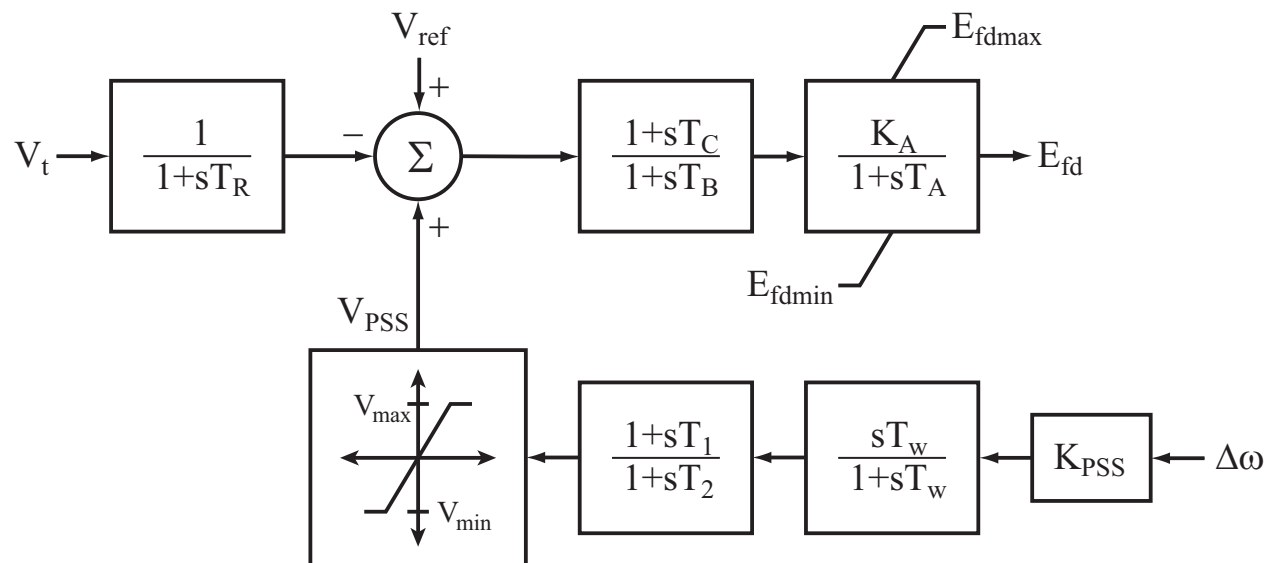
where $\phi(t; \lambda)$ satisfies the dynamic model.

- 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

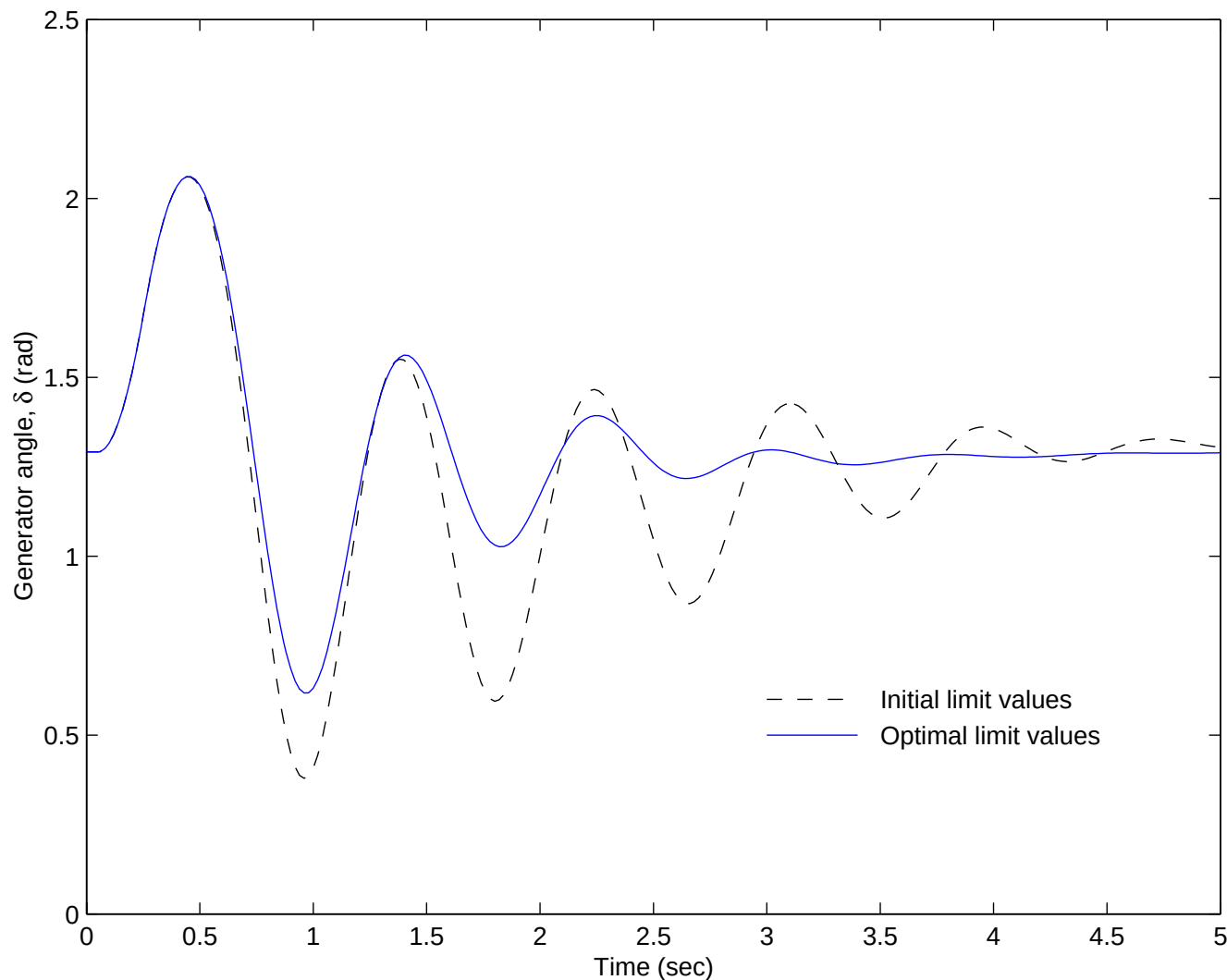
What values of PSS output limits give best damping?



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

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

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

where

$$g^{(j)}(x, y) = \begin{cases} g^{(j-)}(x, y) & y_{s,j} < 0 \\ g^{(j+)}(x, y) & y_{s,j} > 0 \end{cases} \quad j = 1, \dots, s$$

Trajectory sensitivity computation



Smooth sections of trajectories evolve according to

$$\dot{x} = f(x, y)$$

$$0 = g(x, y)$$

Differentiating with respect to x_0 gives

$$\dot{\Phi}_x = \frac{\partial f}{\partial x}(t)\Phi_x + \frac{\partial f}{\partial y}(t)\Phi_y$$

$$0 = \frac{\partial g}{\partial x}(t)\Phi_x + \frac{\partial g}{\partial y}(t)\Phi_y$$

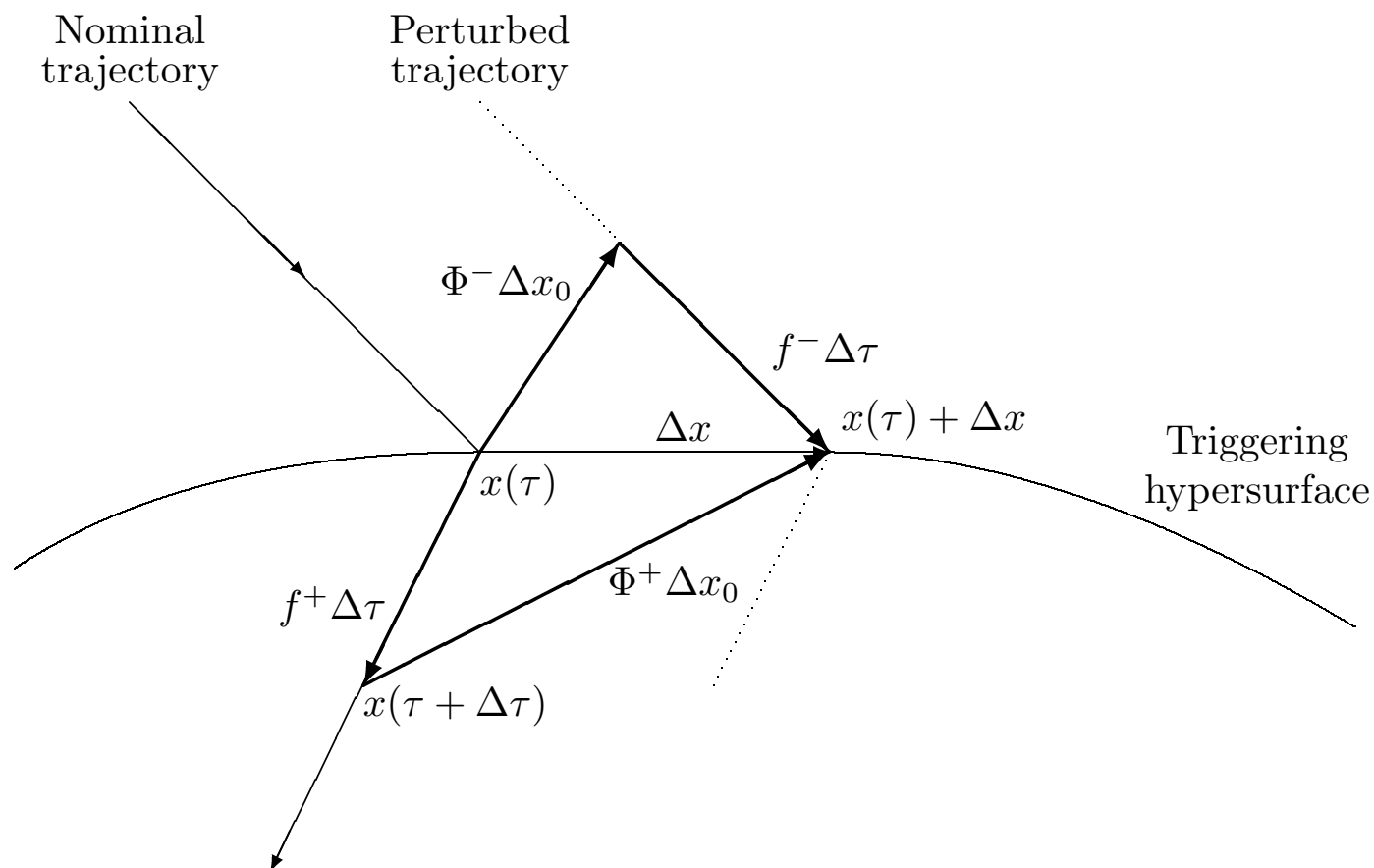
Initial conditions

$$\Phi_x(t_0) = I$$

Trajectory sensitivities at events

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

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



Grazing and time-constraint formulation



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

Grazing

$$\phi(t_g; \lambda) - x_g = 0$$

$$b(x_g) = 0$$

$$b_x(x_g)f(x_g) = 0$$

Time constraint

$$\phi(t_1; \lambda) - x_1 = 0$$

$$\phi(t_2; \lambda) - x_2 = 0$$

$$b(x_1) = 0$$

$$b(x_2) = 0$$

$$t_1 - t_2 - \tau_{spec} = 0$$