Power Systems Engineering Research Center

PSERC Background Paper

Modeling Post-Disturbance Consequences: Uncertainty in Power System Dynamic Simulation

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Power systems are frequently subjected to large disturbances such as lightning strikes and feeder trips. Dynamic response of the power system to these disturbances may involve large deviations from normal conditions, or even instability. Therefore, analysis of dynamic behavior through modeling plays an important role in understanding historical events (such as the recent U.S./Canadian blackout), and planning and operating power systems.

Planners study dynamic performance to determine appropriate strategies for alleviating, or at least minimizing, stability-induced system constraints. Considerations include re-tuning generator control loops, sizing and siting FACTS devices, and design of special protection schemes. In an operating environment, the goal is to circumvent more immediate stability-related risks. For example, operators are interested in determining the influence of generation or transmission outages on stability margins – the “distance” between the current operating point in a power system and the point where system instabilities may occur, perhaps leading to serious system problems such as blackouts.

Such analysis of dynamic behavior is necessarily conducted using models.[1] Actual system behavior is inferred from the simulated response of system models formed from many individual component models. This simulated behavior influences our understanding of historical events, and the planning and operating decisions to maintain system stability in the future; therefore, model accuracy is very important.

Model validation plays a crucial role in assessing and improving model accuracy. Following large disturbances, actual measured behavior is compared with that predicted by model-based simulation. Discrepancies can be used to identify model parameters

[1] Empirical studies requiring purposefully imposed disturbances on the system are impractical and dangerous!

that are not reflective of actual component response, and to provide improved estimates of parameter values. For example, this process has identified cases where generator parameters provided by manufacturers were of questionable accuracy. Investigations of generator control loops have revealed discrepancies between design and implementation.

Many parameters can never be known with absolute certainty. Modeling customer loads provides a classic example. Loads are continually varying. Even though the dynamic nature of individual loads, such as motors, may be well documented, the mix of load types is never certain. Yet it has been found that load characteristics often have a significant effect on dynamic performance of a power system.

Unmodeled effects may also profoundly influence system dynamic performance. During the August 14 blackout, a crucial event occurred when the Hanna-Juniper line sagged into a tree. It's unlikely that anyone would have thought to model that tree in prior system studies! It is also common for hidden (unmodeled) failures in protection schemes to play an important role in major disturbances.

Analysis of power system dynamics must assess two forms of uncertainty: relatively small deviations in values of modeled parameters, and large unmodeled effects. Addressing the latter involves statistical sampling techniques that are appropriate for rare events. This paper focuses on the former, and considers the significance of parameter uncertainty, along with techniques for assessing that significance.

Small parameter variations allow many possible outcomes around the nominal trajectory.[2] Figure 1 provides an example. If the system is stable with converging dynamic solutions (i.e., has a large stability margin), the bound will be tight as the collection of possible trajectories closely tracks the nomimal trajectory. Alternatively, a wide bound will result if the system is on the verge of instability and the collection of trajectories begin to diverge from the nominal trajectory. Furthermore, parameter uncertainty becomes extremely important if it induces a large system event. Under some circumstances such an event may lead to a cascade of similar events, as witnessed on August 14th. Referring again to Figure 1, if we assume that undervoltage load shedding occurs if the voltage falls below 0.875 pu, then, according to the nominal trajectory, no load shedding would occur. However, the uncertainty bound intersects the undervoltage threshold, indicating the possibility of load interruption.

Probabilistic techniques

It is often useful to quantify the possibility of an event, such as load interruption, through the calculation of its probability. With knowledge of the relative probabilities of possible parameter values, the probability of a particular outcome and the range (and bound) of possible outcomes can usually be calculated. The traditional approach to computing a

[2] The nominal trajectory corresponds to the best estimate of parameter values.

bound, such as that shown in Figure 1, is to perform repeated simulations using different possible parameter values.

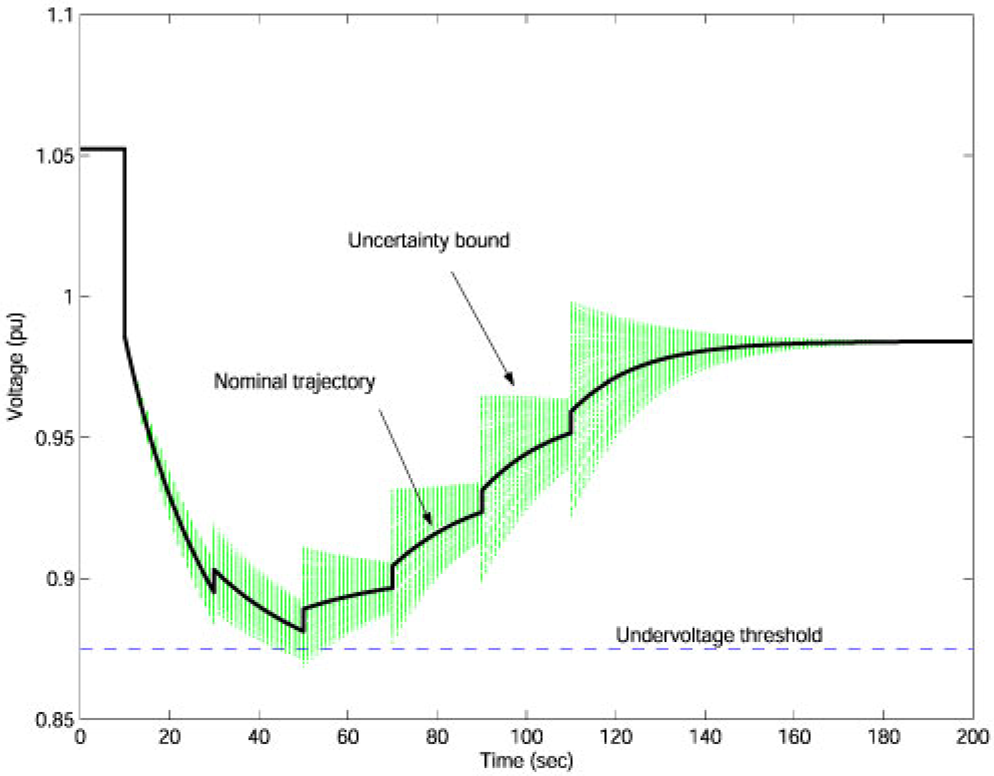

Figure 1: Example of trajectory bounds. Modeling is used to understand the effects of an event. In this case, an event occurred about ten seconds from time zero. This figure illustrates the effects of model parameter uncertainty on the model results. The vertical axis gives the "per unit" (pu) voltage relative to a nominal voltage of one. The dark line is the nominal or "best estimate" of the time path of voltage after the event. The green area represents possible voltage outcomes under different assumptions about the values of parameters in the model. If the undervoltage threshold is interpreted as the voltage level at which the system experiences serious consequences (such as the shedding of customer loads, tripping of transmission lines, etc.), the parameter assumptions make a difference in whether the system survives the event without problems.

A Monte-Carlo technique can be used to generate sets of parameter values chosen randomly from appropriate probability distributions. A simulation is then run for each parameter set. This process often requires significant and intense computation, which can be prohibitive even with very fast computers.

There are two sophisticated techniques designed to efficiently compute bounds and probabilities. The first, based on *trajectory sensitivity analysis*, computes approximate trajectories that take account of parameter variations. The second technique, the *probabilistic collocation method*, uses a few simulations to construct polynomial models to represent the range of possible trajectories, and outcomes derived from these trajectories. (These similar approaches differ slightly in implementation.)

Trajectory sensitivities can be calculated using an enhanced simulation routine. Minimal extra computation is required. These sensitivities provide a first-order approximation of the actual parameter-perturbed trajectory. The error in the approximation is generally quite small. These approximate trajectories can be used in a Monte-Carlo process to quickly bound the range of the trajectory and efficiently estimate the probability of a major event. For the example illustrated in Figure 1, the probability of the voltage falling below 0.875 pu, inducing load shedding is approximately 0.15 for the chosen parameter distributions.

The probabilistic collocation method effectively establishes an approximate polynomial relationship between the uncertain parameters and the trajectory and quantities to be monitored for event triggering (such as when the voltage reaches the minimum voltage or undervoltage threshold in Figure 1.) Based on the theory of Gaussian quadrature integration, it is possible to select a few parameter sets that fully determine the coefficients of that polynomial. As with the trajectory sensitivity approach, this polynomial model can be combined with a Monte-Carlo process to quickly calculate the range of the trajectory and probabilities of major events.

Deterministic Techniques

When the probabilities of different parameter values are not known, or if there is no tolerance for any non-zero probability of a major event, then deterministic approaches may be used to assess worst-case and related scenarios. Worst-case analysis requires the specification of parameter ranges rather than exact values or probabilities. Nonlinear optimization is used to compute the extreme values of chosen system quantities, such as lowest bus voltage (or worst damping of oscillations in the power system resulting from an event), while constraining parameters to their specified ranges. Interestingly, this same approach can easily be adapted to obtain parameter values that give the best performance (i.e., to optimally tune system performance).

Another deterministic approach couples simulation with a nonlinear equation solver such as Newton's method. This so-called *shooting method* solves for the smallest parameter change required to just marginally trigger specified events, such as protection operation. The resulting parameter values constitute a boundary between cases that induce events and those that do not.

Knowledge gained from these deterministic methods provides a measure of the robustness of the system to parameter uncertainty.

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