DOE GMLC Project 1.4.18 “Computational Science for Grid Management”

Use Case 2: Dynamic Security Assessment with Uncertainties

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Context/Need: With the penetration of variable energy resources, the impacts of the resulting uncertainties cannot be ignored in dynamic security assessment (DSA) [1] for both operation and planning applications. Errors in generation and load forecasts can have a random impact on the grid. Therefore, the traditional deterministic-based applications need to be upgraded to consider the forecast errors and be performed in a stochastics manner. Advanced techniques such as smart sampling [2][3] and high performance computing (HPC) are necessary to capture the features in these uncertainties but make computational time tractable. Meanwhile, a middleware framework is necessary for facilitating data communication between uncertainty input and computation modules across different platforms [4]. Such a framework improves the efficiency in developing the DSA application as well as in using the DSA application. In addition, a web-based visualization tool is useful to display computation results and help users to draw insights from the large amount of information.

Problem: The impact of uncertainties introduced by forecasts of energy and loads needs to be considered in DSA within the operation and planning study timeframes. Such uncertainties come from both transmission and distribution levels, particularly with the increasing penetration of intermittent generation and distributed energy resources (DERs).

Applicability:

- Effect of increasing penetration of renewable generation on system stability;
- Effect of DERs and consumer participation on bulk system operation and planning; and
- Optimization of DERs for multiple value streams for the power system.

Mathematical representation: solving a set of DAE equations under contingencies.

1. Differential equations (with classical generator model to illustrate dynamics)

$$\begin{cases} \dfrac{2H_i}{\omega_s}\dfrac{d\omega_i}{dt} = P_{mi} - P_{ei} - D_i(\omega_i - \omega_s) \\ \dfrac{d\delta_i}{dt} = \omega_i - \omega_s \end{cases}$$

where ω_i is the per unit speed for generator *i*, ω_s is the per unit synchronous speed, δ_i is the angular position of the rotor of generator *i* in electrical radians with respect to a synchronously rotating reference, H_i is the inertia constant of generator *i* normalized by the system base, D_i is the damping coefficient, P_{mi} is the mechanical power input of generator *i*, and P_{ei} is the electrical power output.

2. Network algebraic equations

$$Y * E = I_E$$

Where Y is nodal admittance matrix, which will be updated based on each contingency. E is Generator internal voltages and I_E is current injections.

3. Contingency Modeling

Contingencies in the power network changes the Y matrix because of the change in connectivity and impedance.

4. Uncertainty Modeling

Uncertainties have multiple folds of impact. Bulk generation uncertainties (e.g. wind or solar farms) affect the mechanical power P_m; load uncertainties affect the algebraic equations; distributed generation uncertainties affect net load the system needs to support. The latter two propagate through the algebraic equation and eventually affect the electric power P_e. These uncertainties are modeled in the form of probability density functions.

Data Needs: Historical actual data, historical forecast data, forecast data, power system model, generator parameters, and contingency list.

Challenges: computationally expensive due to a large number of DAE simulations and uncertainty scenarios. Traditional Monte Carlo simulation has scalability issues; large-scale statistical data analysis to quantify the sources of uncertainties; seamless data communication; user-friendly visualization and information presentation.

References:

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