RWTH AACHEN UNIVERSITY

E.ON Energy Research Center
ACS | Institute for Automation of Complex Power Systems

Master Thesis / Diplomarbeit:

Sensitivity Analysis in power systems applications

Sensitivitätsanalyse bei Anwendungen in Energiesystemen

The context

Modern power systems are becoming more and more uncertain and complex as new technologies proliferate. Many aspects of power system modelling, analysis and operation may be affected by these intrinsic uncertainties, whose impacts and importance deserve a careful analysis and quantification. As a consequence, traditional *deterministic* approaches towards power system applications (e.g., stability and security assessment, grid management and control, etc.) are no longer able to adequately represent the true system performance. On the other hand, accounting for the *stochastic* behavior (i.e., randomness) of complex power systems calls for the need and development of suitable analysis tools based on probabilistic studies. This way, the uncertain knowledge of the system can accurately be taken into account and the effect of the system uncertainties on the overall system behavior can be quantitatively evaluated.

The challenge to tackle

Many sources of uncertainty may be identified in power systems: spatial-temporal natural (i.e., weather-related) and artificial (e.g., due to the consumers' behavior) variations, forecast and monitoring errors, physical system parameter estimation, etc. To address the uncertainty assessment problem, an effective tool is Sensitivity Analysis (SA), defined as "the study of how the uncertainty in the output of a model can be apportioned to different sources of uncertainty in the model input". In practical terms, SA can instructively inform on the relative contributions of each model input in driving (i.e., affecting) the total model output variation (Figure 1).
SA applied to power systems has often adopted a so-called local (or One-at-A-Time, OAT) approach (e.g., in [1]), mainly based on computing partial derivatives of the model output with respect to each of the model inputs evaluated at a nominal/operational/baseline point. Similar local approaches involve evaluating the model output response by keeping all the model input factors fixed except the one that is being perturbed (hence, the name "One-at-A-Time"). Overall, these local/OAT approaches, though very intuitive and easy to code, have two main drawbacks. First, if the function describing the model is nonlinear with respect to its inputs, then the partial derivative will change depending on which operational point has been chosen to evaluate it. As such, a derivative based sensitivity measure is likely to change (also dramatically) as we move away from the baseline (i.e., the sensitivity measure so obtained is valid only for small changes of the inputs and in a small neighborhood). Second, if there are interactions between model inputs (and in complex systems it is very likely to be the case), no local/OAT approach is able to efficiently capture them, indeed because the model inputs are varied independently (one at a time) and the model interactions are not allowed to emerge.

Surprisingly, the majority of the SA methods applied in the power system domain rely on local/OAT measures also when studying non-linear systems [2].

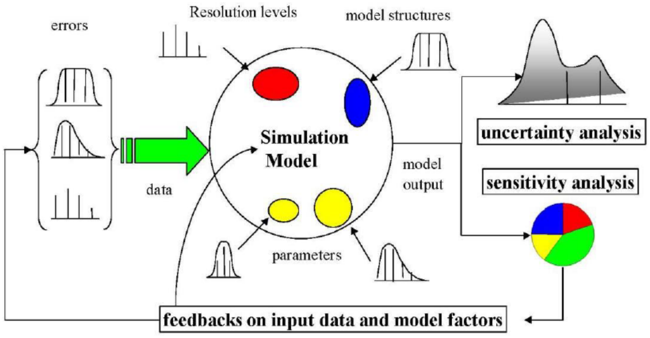

Figure 1 Intuitive explanation of uncertainty and sensitivity analysis. Given the uncertainty in the model inputs (measurement errors, different resolution levels, alternative model formulations, model parameter variation, etc.), the uncertainty analysis is the study of *how* the uncertainty in the model inputs propagates through the model to generate an empirical distribution of the system output of interest (the grey histogram). After the output uncertainty has been characterized (e.g. by its mean and variance), a sensitivity analysis is carried out to quantitatively detect *how much* each model input affects the total output variation. For example, in the picture the most influential model input (the green slice of the pie chart) is the errors in the data, whose uncertainty is responsible for almost one third of the total output variation.

A possible approach

Opposed to the local/OAT approaches, another family of SA methods have been recently developed, which take into account the overall range of variation of the model inputs by sampling them at the same time, instead of one at a time. These methods lay under the umbrella of the so-called Global Sensitivity Analysis (GSA), which can be applied irrespective of the linearity degree of the model and informs the analyst about factors' global influence in terms of their contribution to the variance of the model output, including the effect of interactions among them. GSA approaches can be considered as a requisite for performing a *valid* sensitivity analysis when models are characterized by nonlinearities and interactions.

To understand the difference between Local and Global SA, Figure 2 provides with an intuitive explanation in terms of ability to explore the overall variability range of the model inputs. It is evident how OAT approaches are not able to effectively explore a multidimensional space (i.e., taking into account the full range of input variability) and any type of result deriving from a local SA would be constrained to the operational point where the model has been studied.

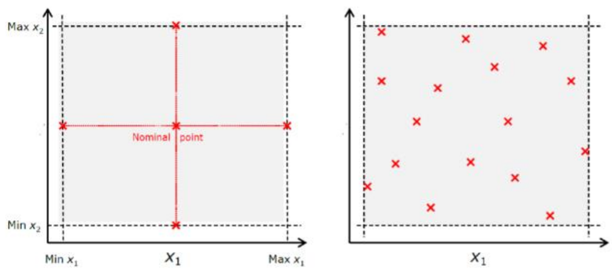

Figure 2 Intuition of the difference between Local and Global SA. Assume you have two uncertain model inputs (x_1 and x_2), which vary between minimum and maximum values. For analyzing the sensitivity of the model output to each of the two model inputs, the analyst would be interested to explore the set of *all* the possible combinations of values of the two input factors (the 'input space'), which in this case turns out to be a two-dimensional plane. However, with an OAT approach (left part), the combinations of values at which the model is studied (the red crosses) would actually lay simply along two perpendicular lines and the remaining part of the input space would remain not explored at all. Instead, with a global approach (right part) the input space would be more effectively investigated. For high-dimensional models, OAT approaches happen to be ineffective and not robust in terms of exploration of the input space, since only a really small portion of the total variability of the model inputs can be studied. Moreover, no interactions can be captured and all the conclusions derived from a local approach would be valid only in a small neighborhood around the operational point at which the model is studied.

The overall goal of this thesis is to perform both Local and Global SA of specific power system applications, to critically highlight the main differences of the two families of methods. The applicative case study to be analyzed under a SA perspective can be shaped according to the knowledge/interest/research field of the student.

Your tasks (and therefore the skills you will acquire)

- Analysis of selected literature regarding GSA for understanding its basis and its differences with respect to the Local SA
- Critical literature review on what is the state-of-the-art for performing SA on different power system applications
- Identification of a meaningful applicative case study (already available in the literature or created ad-hoc) to be used for performing Local and Global SA
- Utilization of different GSA methods for showing pros and cons
- Critical comparison of the differences between Local and Global SA approaches when applied to the selected applicative case study (e.g., what are the differences of applying local or global approaches in terms of derived conclusions?)

Your profile

- RWTH student of Electrical Engineering (but students coming from other RWTH faculties or other universities are welcome to apply)
- Basic (but effective!) skills of MatLab and Python
- Previous knowledge of power system analysis as well as general knowledge of statistics is a plus

Notes

The supervision will be done in English.

References

[1] F. Tamp and P. Ciufo, "A Sensitivity Analysis Toolkit for the Simplification of MV Distribution Network Voltage Management," in *IEEE Transactions on Smart Grid*, vol. 5, no. 2, pp. 559-568, March 2014, doi: 10.1109/TSG.2014.2300146

[2] A. Saltelli, K. Aleksankina, W. Becker, P. Fennell, F. Ferretti, N. Holst, S. Li, Q. Wu, "Why so many published sensitivity analyses are false: A systematic review of sensitivity analysis practices", in *Environmental Modelling & Software*, vol. 114, pp.29-39, 2019, doi: https://doi.org/10.1016/j.envsoft.2019.01.012.

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