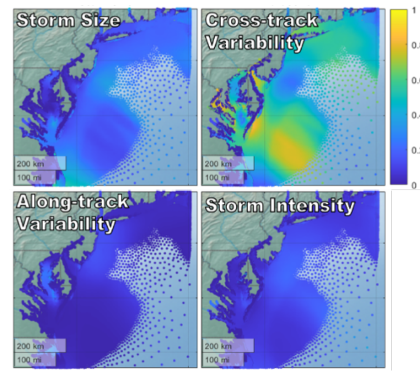
quoFEM Application Summary (V4.1)

The Quantified Uncertainty with Optimization for the Finite Element Method (quoFEM) application facilitates Uncertainty Quantification (UQ) analyses on a wide range of computational simulation models. The application provides a user-friendly interface with OpenSees and other simulation applications and easy access to pre-implemented advanced probabilistic analysis algorithms. quoFEM currently supports global sensitivity analysis, reliability analysis, Bayesian parameter calibration, and surrogate modeling, along with Monte Carlo-type forward propagation and deterministic optimization techniques. quoFEM aims to accelerate the adoption of UQ techniques in the natural hazards engineering community by making robust and practical UQ algorithms more accessible to researchers and practitioners.

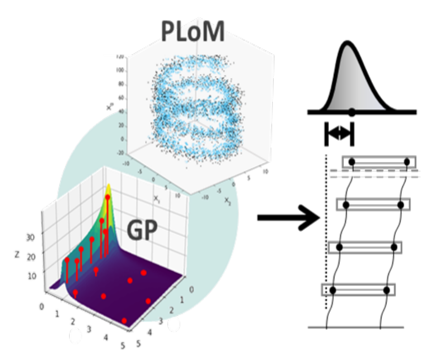
USE CASES

Global Sensitivity Analysis for High-dimension Outputs



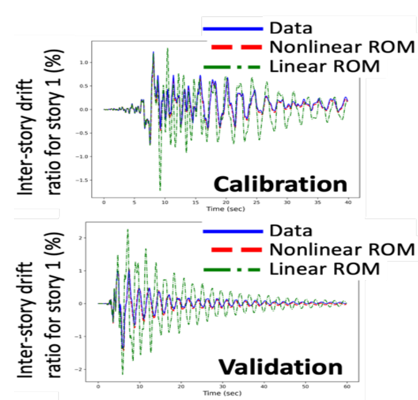
Sensitivity analysis can be performed to identify parameters of the model that are the most influential to the response of interest. Two algorithms with different coverage and benefits (speed or accuracy) are supported in quoFEM. One of the algorithms is combined with dimension reduction techniques to handle high-dimensional outputs. Application examples include a sensitivity analysis of hurricane model parameters to quantify their contribution to storm surge water elevation. In this example, sensitivity analysis for a 2 million output system was performed in approximately 5 minutes using a sample of only 500 simulations.

Surrogate Modeling of High-fidelity Simulation Models



Two different surrogate methods are supported in quoFEM: Gaussian Process (GP) and Probabilistic Learning on Manifolds (PLoM). To facilitate use of high-fidelity models in regional simulations and design studies, quoFEM helps users develop surrogate models that are trained on detailed simulation models (e.g., using finite element methods) and can then be integrated and run in large-scale regional models at a fraction of the computational cost of the detailed models. Smart sampling techniques (i.e., adaptive design of experiments) are implemented to further reduce the number of computationally intensive simulation runs in training a surrogate model.

Calibration of Numerical Simulation Models



quoFEM offers methods to perform deterministic or probabilistic (Bayesian) calibration of the parameter values of computational models. In addition to gradient-based deterministic calibration, a gradient-free deterministic optimization method from Dakota (Pattern Search) is integrated in quoFEM. In one example Bayesian calibration was employed to calibrate reduced-order models that emulate the nonlinear seismic response history of a multi-story building. Sample values from the resulting parameter distributions can be used to make predictions that incorporate parameter estimation uncertainty using quoFEM or other SimCenter tools.

CURRENT CAPABILITIES

Uncertainty Quantification: Samples the prescribed random input variables and obtains realizations of the outputs by executing the workflow with each input realization from the generated sample. The underlying UQ engines let you leverage the following techniques in your research:

- Forward propagation: Define a set of random input parameters and perform Monte Carlo simulations to obtain a corresponding sample of output parameters.
- Sensitivity analysis: Measure the influence of the variability in the response output to uncertainties in the model input parameters.
- Reliability analysis: Algorithms to estimate the probability of exceeding a failure surface.
- Surrogate models: Generate training data, develop, and utilize surrogate models using Gaussian Process and Probabilistic Learning on Manifolds techniques.
- Deterministic calibration: Optimize the input parameter values of a computational model to achieve the closest possible alignment between its outputs and the provided dataset.
- Bayesian calibration: Update the uncertainty in the input parameter values for a computational model based on observed data.
- Model class selection: Determine the most appropriate computational model from a set of candidates that best represents observed data.
- Multi-fidelity Monte Carlo Simulation: Ability of user to utilize lower cost computational models with higher fidelity models to reduce computational time yet preserving same accuracy.
- Bayesian Calibration of Hierarchical Models: Ability to calibrate a model to data from multiple experiments and to jointly capture the variability in the model parameters.
- Surrogate-aided Bayesian Calibration: Ability to efficiently train a surrogate model approximation and use it to sample from the updated probability distribution of the parameters for models with high computational cost.

Response Simulation: Defines the modeling and analysis options that will be used to perform the numerical simulation, e.g., geometry, connectivity, materials, time integration strategy, convergence, damping options. quoFEM supports the use of various computational tools (e.g., OpenSees, Python, or other numerical simulation tools) to simulation the response and collect the requested output quantities.

UPCOMING CAPABILITIES

Open to user requests – join the discussion at https://github.com/orgs/NHERI-SimCenter/discussions/categories/quofem.

MORE INFORMATION

The software application, examples, and Information about previous releases can be found in the documentation accessible from the quoFEM website at: https://simcenter.designsafe-ci.org/research-tools/quofem-application/.

This material is based upon work supported by the U.S. National Science Foundation under Grant No. (1612843 & 2131111).