Reliability & Sensitivity Analysis using **quoFEM**

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NSF award: CMMI 1612843

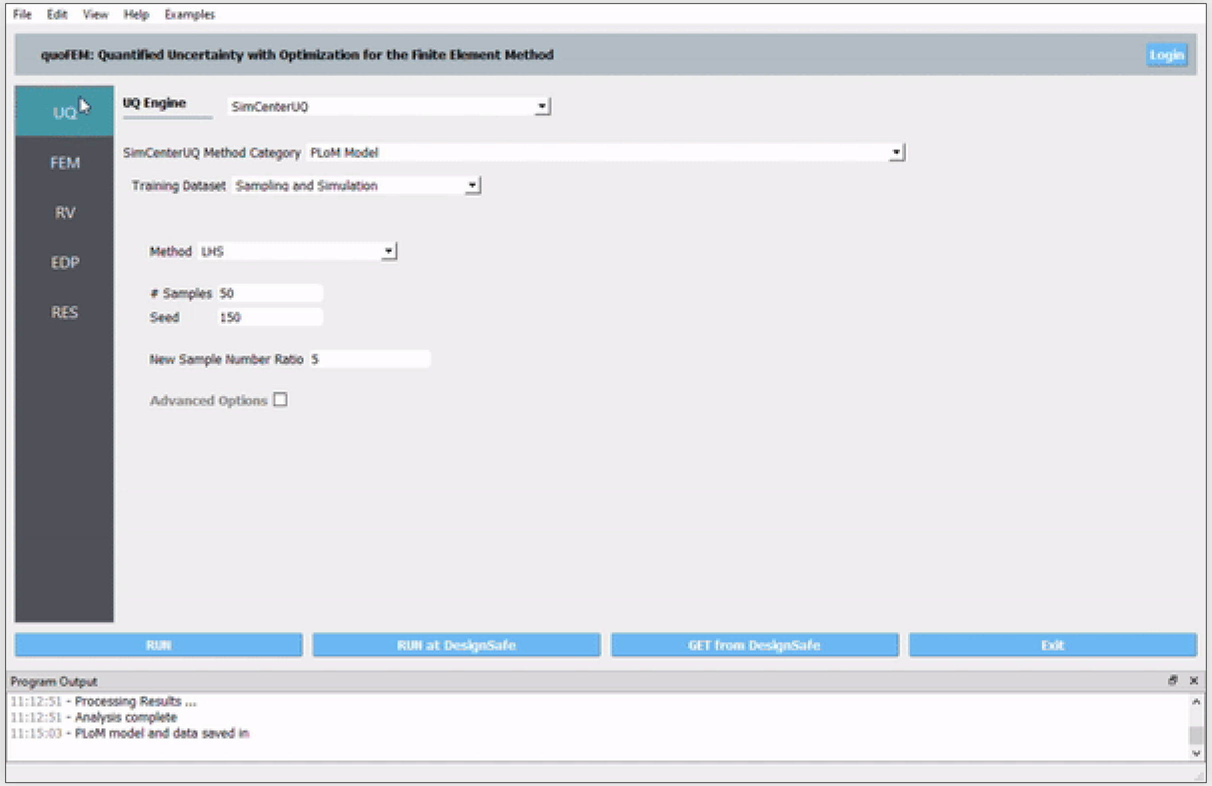
NHERI

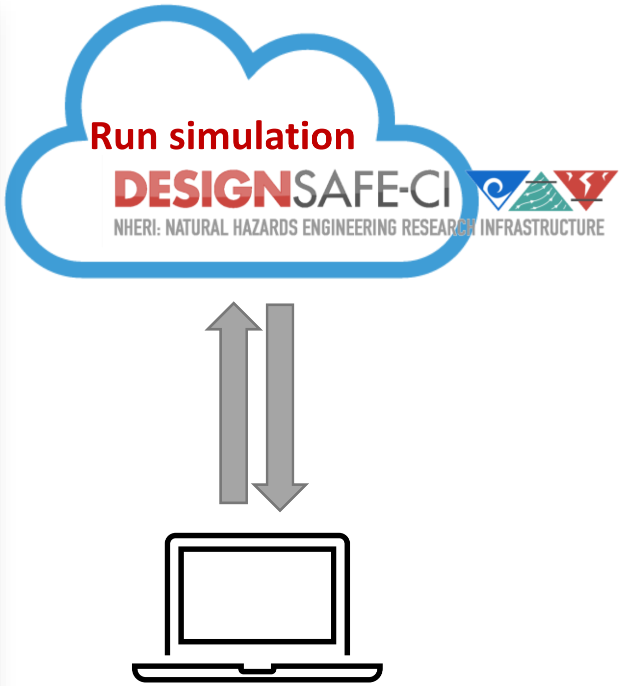
Virtual experimental facility

SimCenter

Develop **Opensource software tools** for researchers in **Natural hazard engineering**

Researchers
Industry
Government Agencies

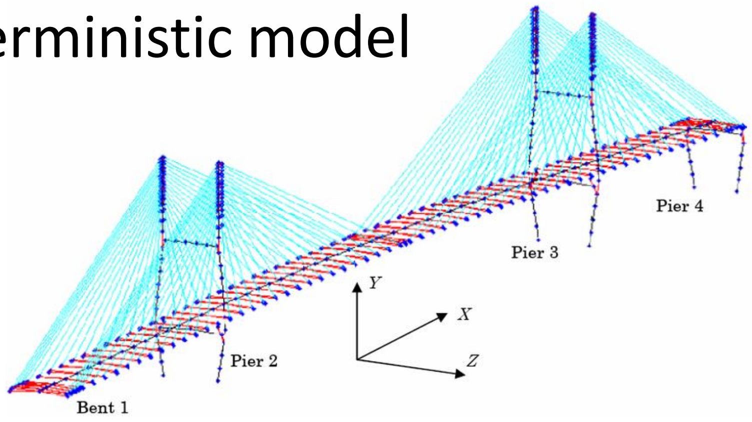




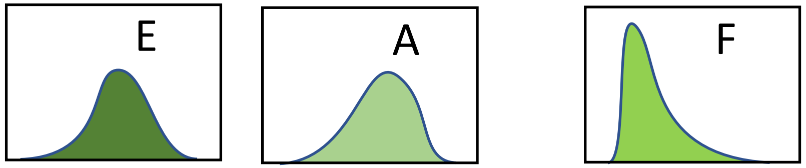
SimCenter Tools

UQ-enabling Tool

Deterministic model



Random Variables



+ UQ/Optimization Analysis

SimCenter Tools

Hazard-specific Modeling and Analysis Tools

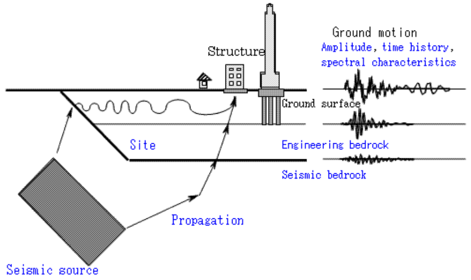
EE-UQ

WE-UQ

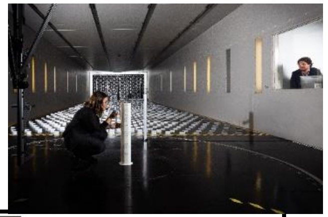
HydroUQ

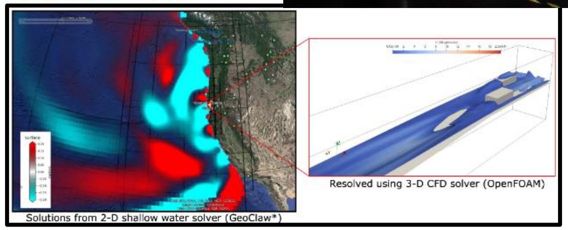
Hazard models

Your own model



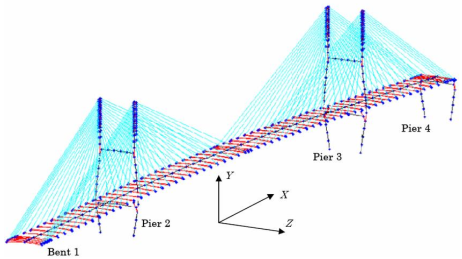
or hazard scenario generator





Structure models

Your own model



or building model generator

+ UQ analysis

+ Damage and Loss Analysis

PBE

SimCenter Tools

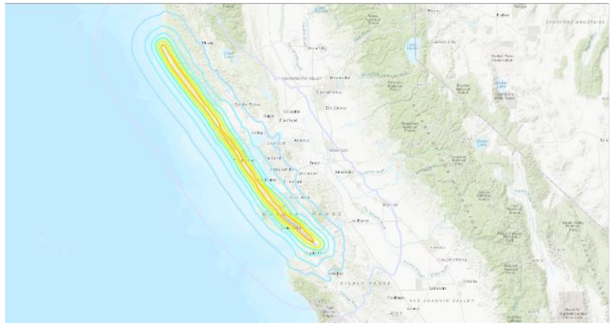
Regional-Scale Risk Management Tool

R2D

Multi-hazard Simulation

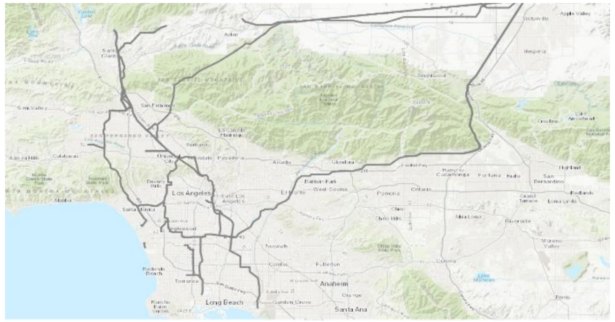
Multi-asset Analysis

Earthquakes

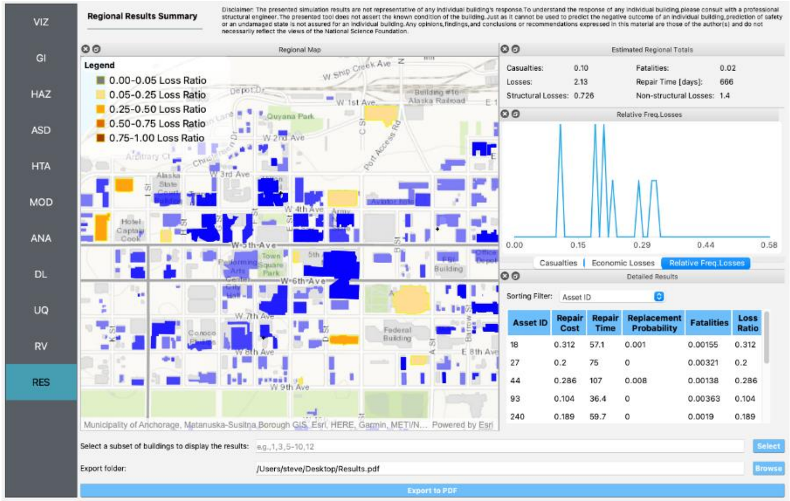


Buildings

Hurricanes



Lifeline Networks

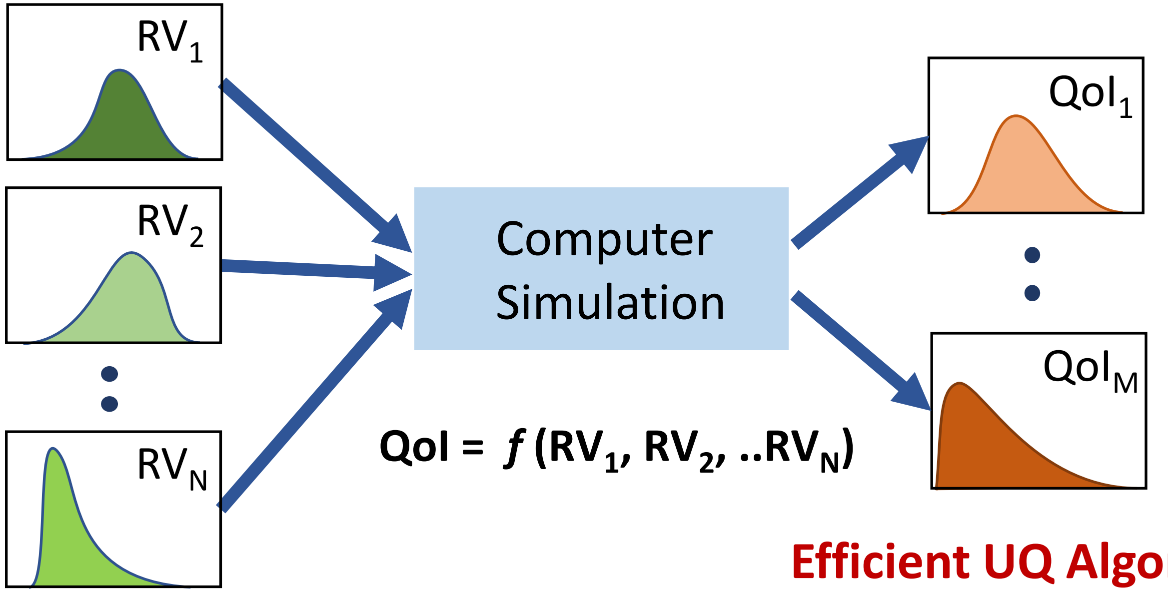


e.g. "The buildings are mostly likely in moderate damage states. The non-structural damage would dominate the economic losses. The repair costs range from 1% to 7% of the total replacement costs, and the repair time range from 1 to 20 days."

SimCenter Tools

SimCenter's scientific workflow

We are running UQ workflow



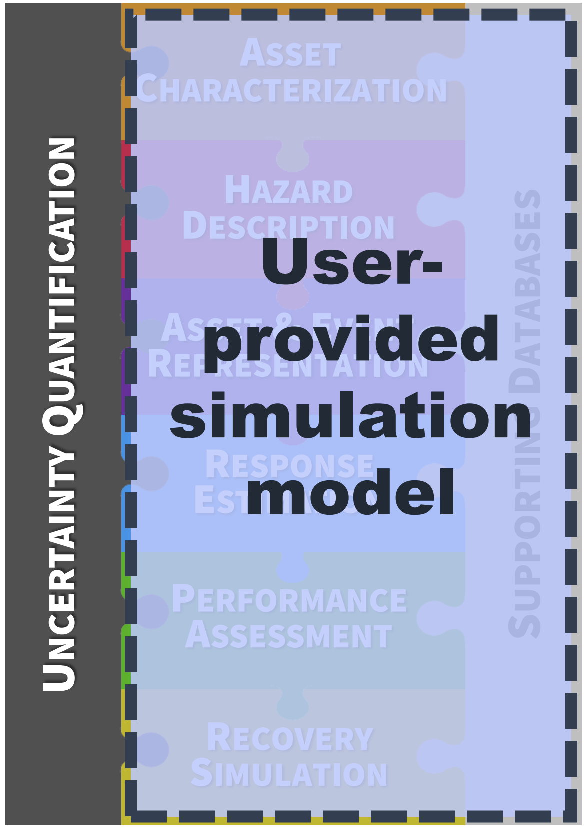
QoI = $f\,(RV_1, RV_2, ..RV_N)$

Mean
Std.Deviation
Kurtosis
Skewness
Probability of failure
Sensitivity
PDF, CDF
...

Efficient UQ Algorithms + HPC

Introduction to quoFEM

quoFEM:
Quantified Uncertainty with Optimization for the Finite Element Method



EE-UQ, WE-UQ, Hydro-UQ, PBE, R2D
- Helps generate event scenarios for specified hazards and provides seamless workflow

quoFEM
- Flexible to problem/model types
- Strong UQ capacity

quoFEM (v.3.0)

FEM Engines

- OpenSees
- FEAPpv
- OpenSeesPy (general python interface)
- Custom
- Surrogate Model

Methods

- Sampling
- Global Sensitivity
- Parameter Estimation
- Calibration
- Custom UQ
- Surrogate Modeling

Algorithms

- Latin Hypercube Sampling
- Monte Carlo
- Gaussian Process Regression
- Polynomial Chaos Expansion

- Probability model-based approximation
- Smart Monte Carlo method

- Local Reliability (FORM, SORM,..)
- Global Reliability (Active learning-based)
- Importance Sampling

- OPT++GaussNewton
- NL2SOL

- DREAM
- TMCMC

- Custom UQ algorithm

- Gaussian process surrogate modeling
- Gaussian process multi-fidelity modeling
- Probabilistic learning on manifolds

Orange: Dakota engine (Sandia National Lab)

DAKOTA

Sandia National Laboratories

Blue: In-house developed program

quoFEM (v.3.0)

FEM Engines

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- Custom
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Methods → Algorithms

Sampling
- Latin Hypercube Sampling
- Monte Carlo
- Gaussian Process Regression
- Polynomial Chaos Expansion

Global Sensitivity
- Probability model-based approximation
- Smart Monte Carlo method

Reliability
- Local Reliability (FORM, SORM,..)
- Global Reliability (Active learning-based)
- Importance Sampling

Parameter Estimation
- OPT++GaussNewton
- NL2SOL

Bayesian Calibration
- DREAM
- TMCMC

Custom UQ
- Custom UQ algorithm

Surrogate Modeling
- Gaussian process surrogate modeling
- Gaussian process multi-fidelity modeling
- Probabilistic learning on manifolds

Reliability Analysis

Gives CDF value $(1 - P_f)$

Dakota theory manual Section 2.1

- **Local reliability**
  - Mean value (MVFOSM)
  - Most Probable Point (Design point)
    - Exact MPP search – traditional FORM/SORM
    - Approximate MPP search – faster convergence, less accuracy

Optimization: sequential quadratic programming (SQP) and nonlinear interior-point (NIP) optimization

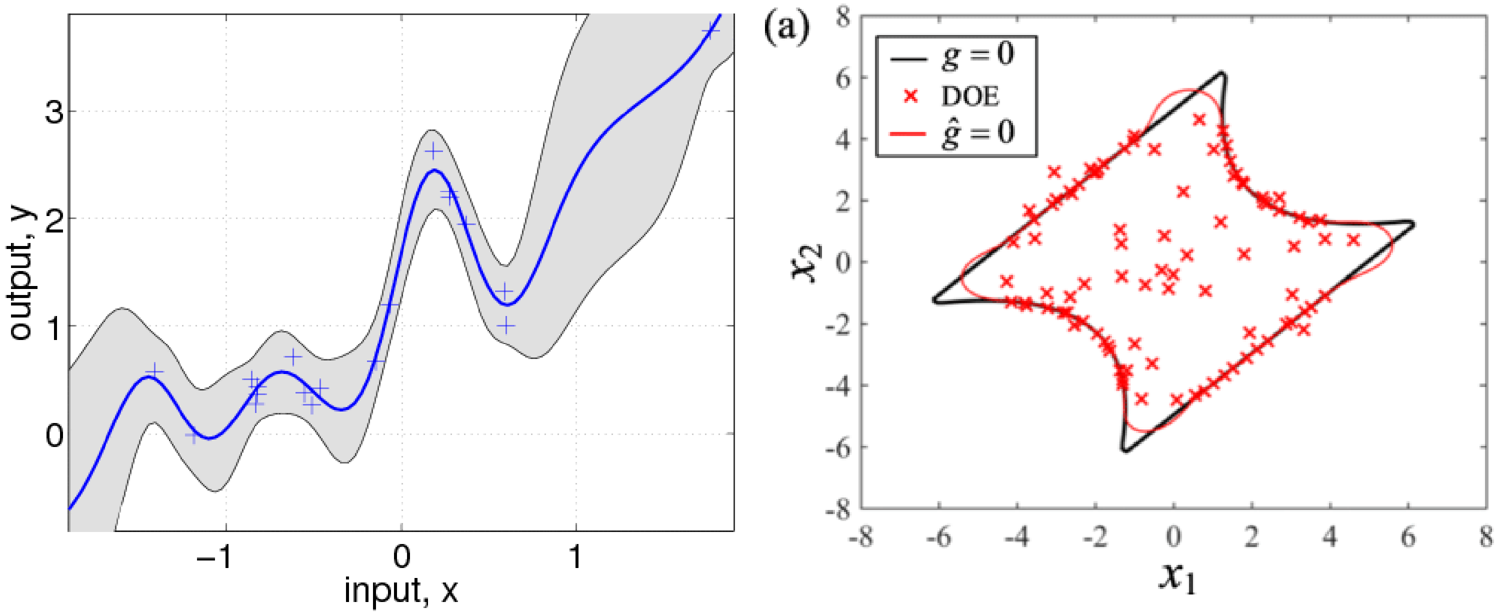
Reliability Analysis

[Dakota theory manual Section 2.2.2, Chapter 8]

- **Global reliability**

  - Use surrogate model (Gaussian process) to approximate limit-state function

    → Works well when the limit-state function is multi-modal / highly nonlinear



Reliability Analysis

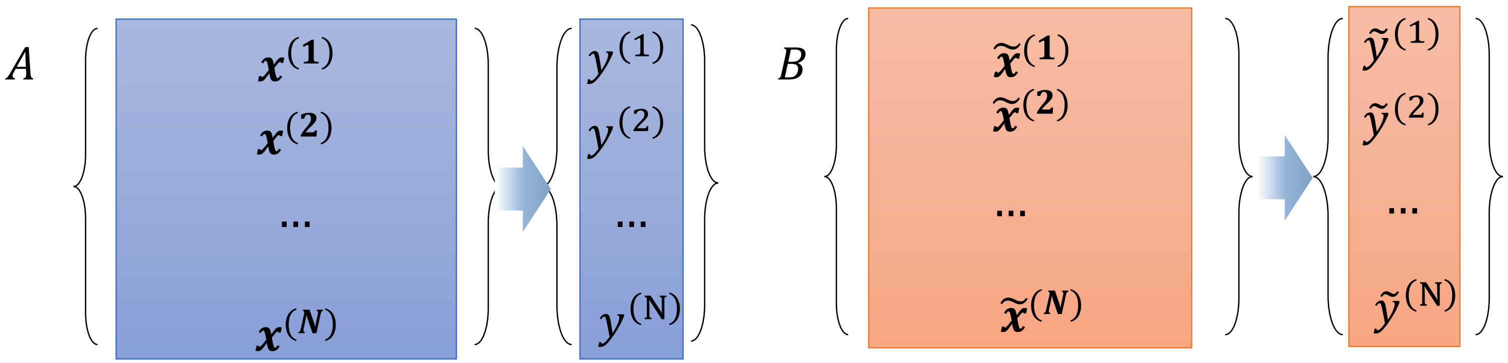
- **Importance sampling**
  - Basic/adaptive/multimodal-adaptive

[Dakota theory manual Section 2.2.1]

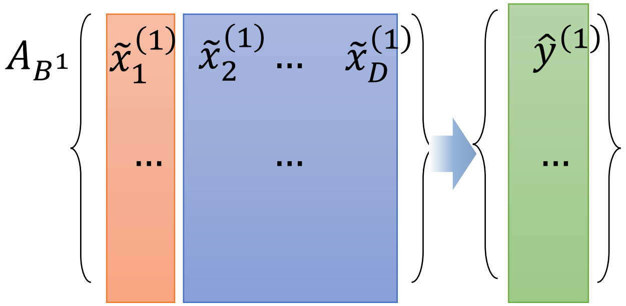
Global Sensitivity Analysis

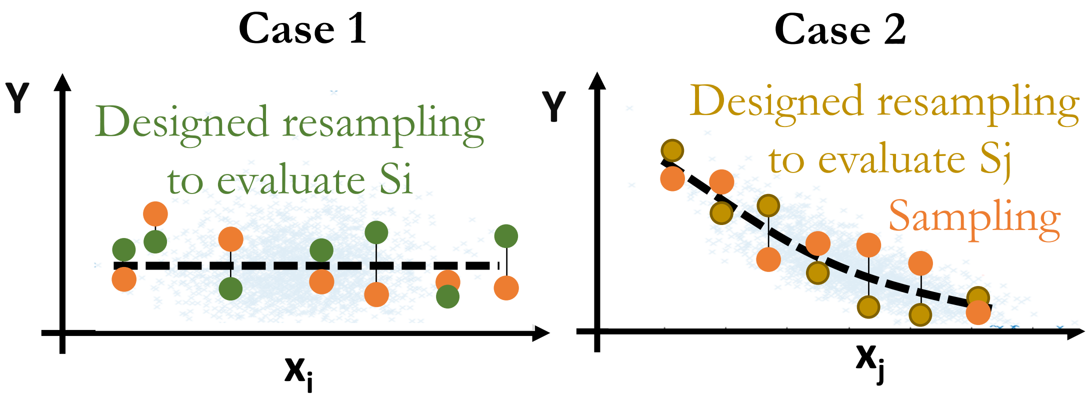
- **Smart Monte Carlo (Dakota Engine)**

Two independent N sample set



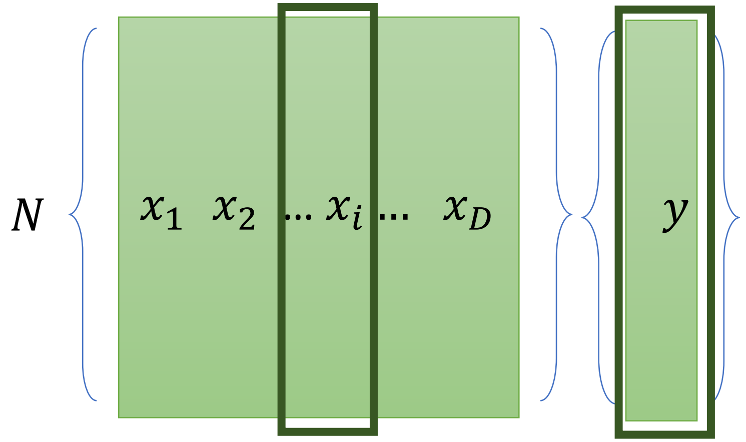
Designed sample set to estimate Sobol indices of X_1





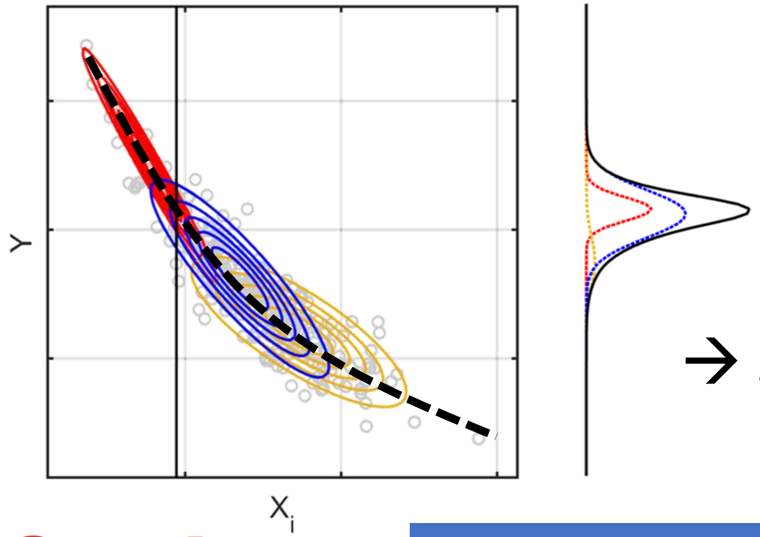
Global Sensitivity Analysis

- **Probability-mode based GSA (SimCenter UQ engine)**



Estimation algorithm

- Approximate joint distribution of $f(X_i, Y)$ using a Gaussian mixture model (GMM)
- Estimate $\mathbb{E}[\mathrm{Y}|X_i]$ from GMM $f(\mathrm{X}_i, Y)$
- Repeat for different $X_i^{(n)}$ samples to get sample variance

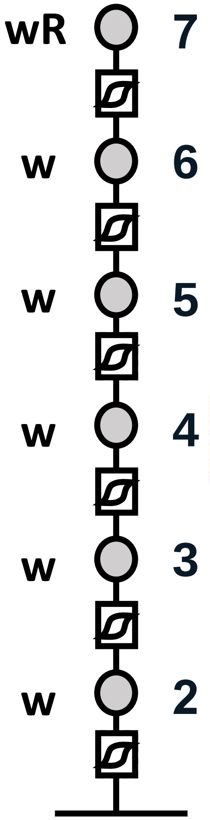


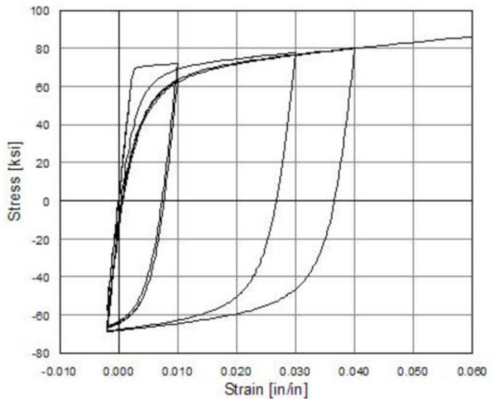
$$\mathbb{V}\mathrm{ar}_{x_i}\left[\mathbb{E}_{\boldsymbol{x}_{\bar{i}}}\left[\mathrm{Y}|X_i^{(n)}\right]\right]$$

→ Supports group-wise sensitivity index

Example1

Structure (Opensees)

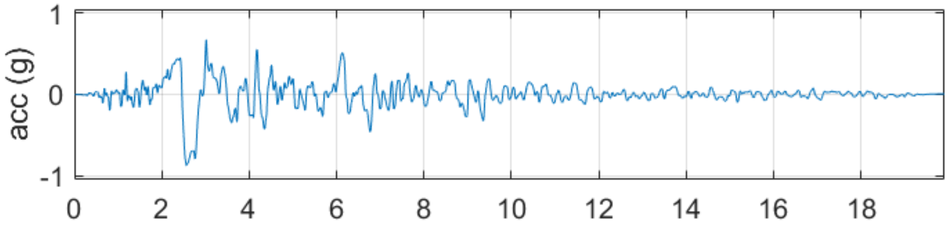




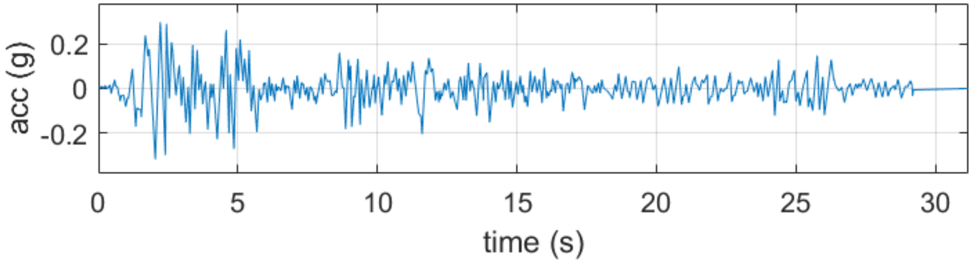
Steel 02 Material

Excitation

Rinaldi
near-field



El Centro
far-field

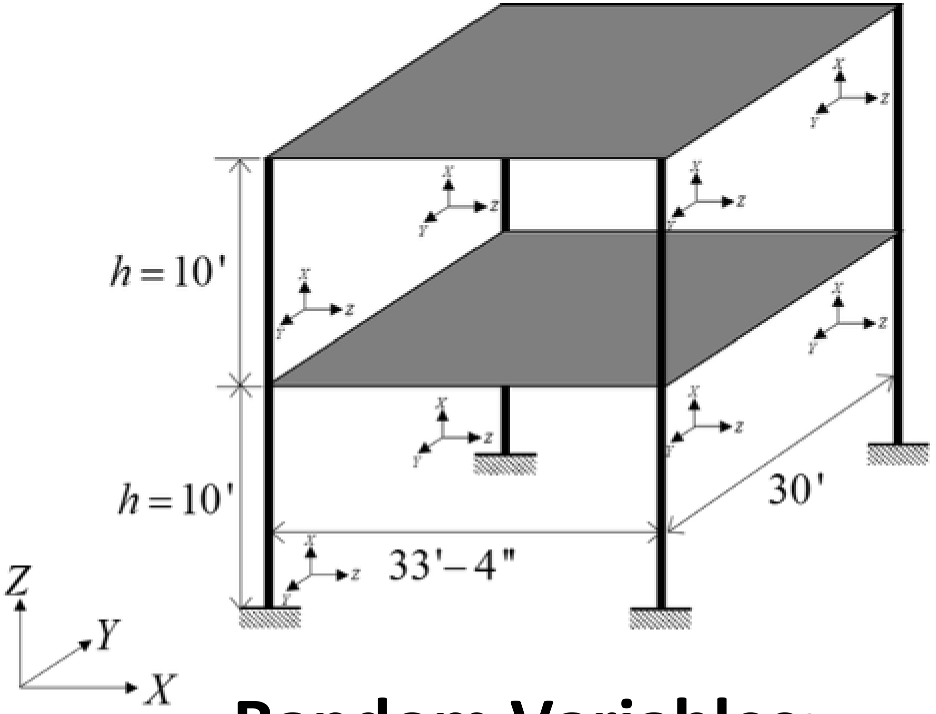


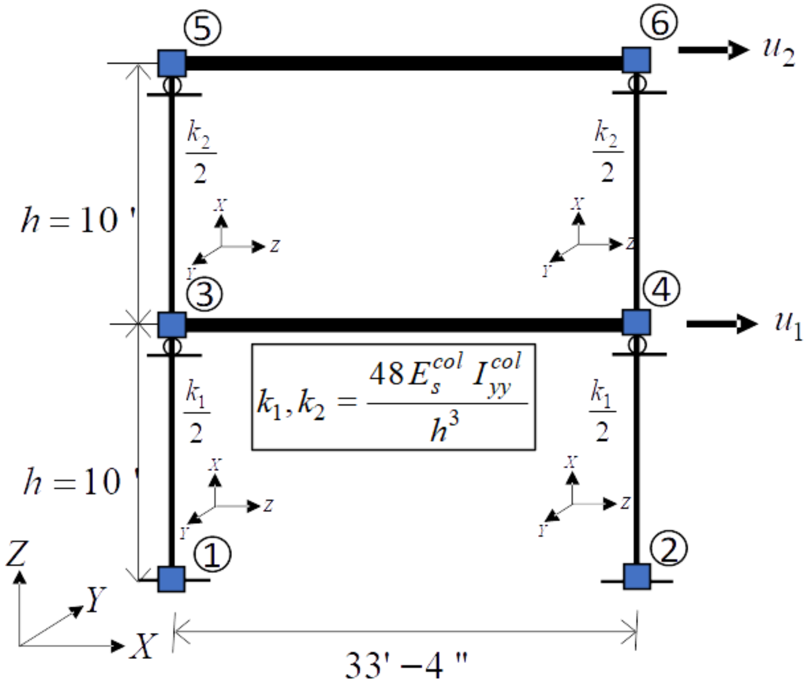
Random Variables

Name	Mean	C.O.V
w	100	0.1
wR	50	0.1
k	326	0.1
Fy	50	0.1
alpha	0.2	0.1
factor (PGA)	0.1	0.1

Example2

Structure (Opensees)





Random Variables:
k1,k2

Quantity of Interest:
Eigenvalue (rad/s) ^{2}

Example3

Truss model written in OpenseesPy