2019 Fall Meeting, AESJ Risk Subcommittee: Bayesian Approach to Risk Assessment

(4) Application of Bayesian Statistics to Source Term Analysis

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The development of surrogate models to predict fission products chemical forms was performed under the support by the Nuclear Regulation Authority of Japan.

Introduction: Severe Accident Simulation

- Source term (or fission products): radionuclides, including physical & chemical forms, released to the environment during a severe accident.
- Source term directly affects the risk assessment of an NPP, including Level II & III PRA, and the planning of emergency preparedness & response.



Introduction: Bayesian Inference

- Bayesian inference: fit a probabilistic model to data, estimate the model parameters, and use the model for future predictions
- Simplest model:
 - Linear Regression using Bayesian parameter estimation



Mathematical form of the Model:

- Clear: parametric Bayesian
- Unclear: nonparametric Bayesian



- Dirichlet process mixture (GPM)
- Gaussian process (GP)

*Both nonparametric Bayesian

JAEA Methodology on Source Term Research



Statistical Surrogate Model

- Integral severe accident codes are designed to bound all important phenomena, so the simulation is generally time-consuming.
- To reveal the relationships between input and output, or the sensitivity (importance) of inputs, a better way is to use a surrogate model (Reduced Order Model) to approximate the SA code.





- A nonparametric Bayesian model: Gaussian Process (flexible and nonlinear)
- Solution Gaussian process defines a distribution (multi-dimensional Gaussian distribution) over functions p(f), which can be updated using Bayes' rule with available data.

Bayes' rule (function-space view): $p(f|\mathcal{D}) = \frac{p(f)p(\mathcal{D}|f)}{p(\mathcal{D})}$

Example of Gaussian Process Regression (The BLUE function predicting better with more data)



* Example is demonstrated using scikit-learn (a machine learning library in Python)



Application of Bayesian Surrogates (1): Bayesian Optimization of Accident Counter-Measures

Procedure of Bayesian Optimization



- Apply the Gaussian process model to optimize severe accident countermeasures (containment venting) of a BWR nuclear power plant.
- Simulation-based Bayesian optimization can help find the best venting conditions (release of fission products to the environment, containment pressure, etc.) with fewer simulations, because the prediction via surrogate model can avoid aimless analysis.



Application of Bayesian Surrogates (2): Source Term Uncertainty and Sensitivity Analyses

- Random-sampling-based uncertainty quantification requires hundreds of code executions, and global sensitivity analysis (GSA) requires much more to investigate the parameter-interactions among various input settings.
- Trained a surrogate model (another nonparametric Bayesian model: Dirichlet process) to predict results of MELCOR, applied to GSA (20000 runs).





Application of Bayesian Surrogates (3):

"Mimic" FP Chemistry in Reactor Coolant System



Conclusions and Thoughts

- Bayesian approaches show its powerful modeling abilities (flexible model structure, avoid overfitting, etc.) to support nuclear severe accident simulations, especially for source term analysis.
 - Uncertainty and sensitivity analyses
 - Optimization
 - Surrogate model
 - Data processing

Simulation-based Risk Assessment

When simulation is, more and more closely, coupled with PRA methods, Machine Learning and Bayesian Approaches also show potentials, in fields of model-building, data-processing, etc.).

Thank you very much for your attention!