Idaho National Laboratory

Acceleration of UQ and PRA with RAVEN Hybrid Model

A. Alfonsi, C. Wang, C. Rabiti, D. Mandelli, P. Talbot, C. Parisi





IRUG 2018 Idaho Falls, 3-4 May, 2018



Outline

- RAVEN overview:
 - General Code Infrastructure
 - UQ and PRA capability needs
- Surrogate Modeling:
 - Overview
 - Validation
 - Optimization
- Hybrid Modeling
 - Automated model selection
- Future Work



RAVEN overview

RAVEN overview

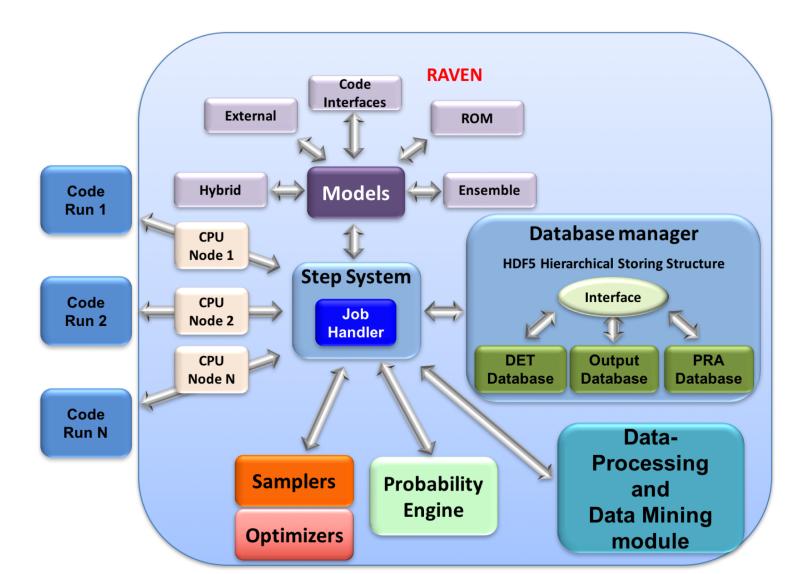


Project Background

- RAVEN development has begun in early 2012. Been supported by:
 - Light Water Reactor Sustainability (LWRS), under the RISMC path-way
 - Nuclear Energy Advanced Modeling and Simulation Program (NEAMS)
 - Nuclear-Renewable Hybrid Energy Systems (NHES)
- The overall goal was to conceive a tool to enable Risk Informed Safety Margin Characterization (RISMC)
 - Evaluating risk (uncertainty propagation)
 - Understanding risk (limit surface, ranking, sensitivity, data mining)
 - Mitigating risk (optimization)

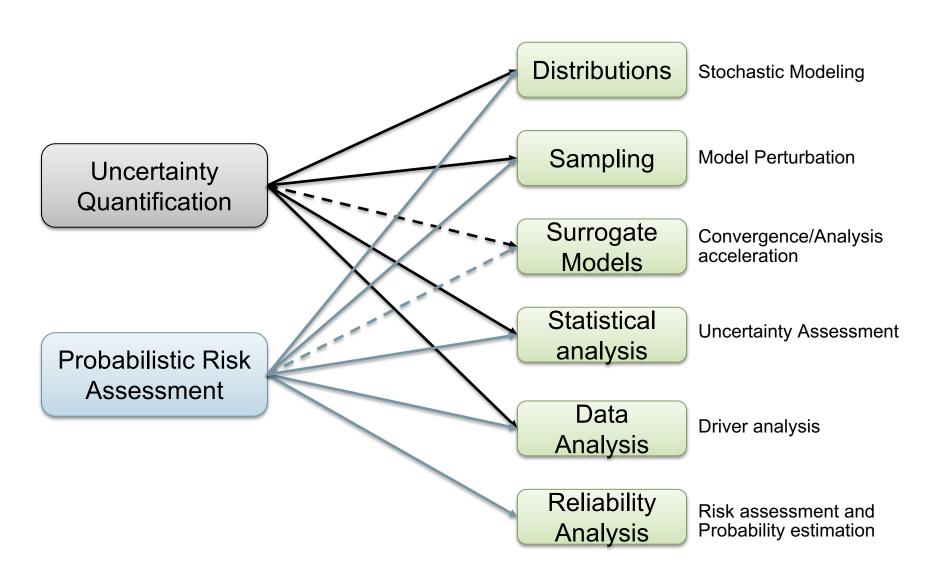


RAVEN Infrastructure





UQ and PRA: Capabilities vs. Needs





DPRA and UQ methodologies

Dynamic PRA and UQ common methodologies



Samplers (Forward)

RAVEN supports many forward samplers

- Monte Carlo
- Grids:
 - equal-spaced in probability and/or in value or custom
 - mixed (probability, custom, value)
- Stratified (LHS type)
 - equal-spaced in probability and/or in value or custom
 - mixed (probability, custom, value)
- Factorial Designs:
 - 2-Level Fractional-Factorial
 - Plackett-Burman
- Response Surface Designs:
 - Box-Behnken
 - Central Composite
- Generalized stochastic collocation polynomial chaos

A different sampling strategies can be associated to each variable separately



Models

RAVEN support five different models' entities:

- ROM (Reduced Order Models). This type of models are constitute by already trained supervised learning algorithms (RAVEN can use data sets for their training)
- External Models. External models are made of python code that use directly the "model" class
- External codes. These are classical third parties codes. The API requires the implementation of writing/reading to/from the input/output files
- Ensemble Model. Assemble of multiple models
- Hybrid Model. Smart Assemble of Surrogate and "high-fidelity" models



ROMs: a Quick Introduction

Consider a set of N data points

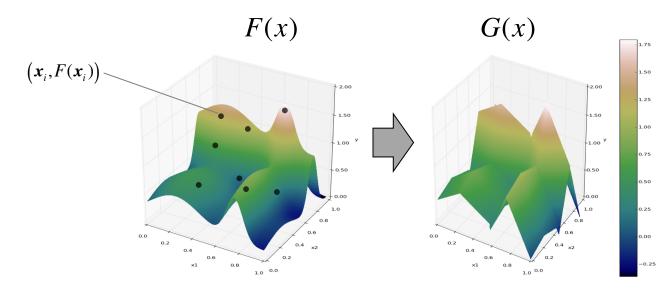
Output: Simulation outcome (success/failure, max clad temperature)

Data

 $(x_i, F(x_i))$ i = 1, ..., N

Inputs: Initial and boundary conditions

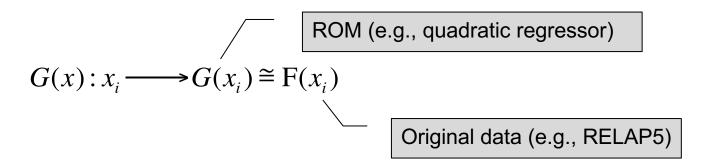
- Build a surrogate model
 - Reduced Order Model $G(x): x_i \longrightarrow G(x_i) \cong F(x_i)$





ROMs: a Quick Introduction

Basically we are trying to reduce the complexity of the original model



- Pros:
 - Much faster computation of the output variable
- Cons:
 - Presence of error in the ROM computed values



Cross-Validation for assessing Surrogate Models validity

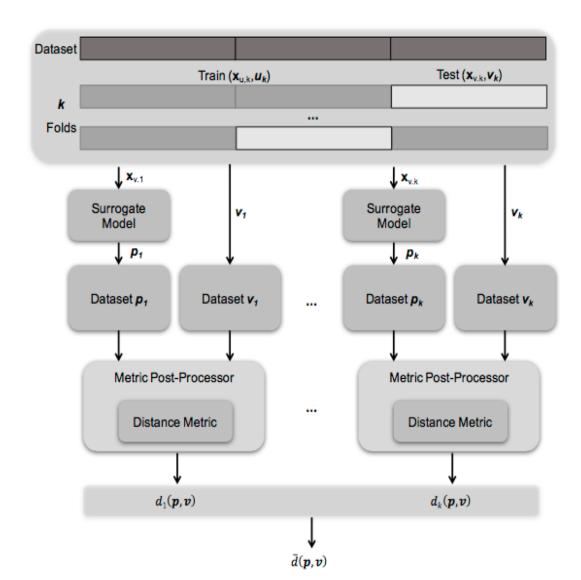
- Take out some of the training set
 - Train on the remaining training set
 - Test on the excluded instances
 - Cross-validation
- Cross Validation

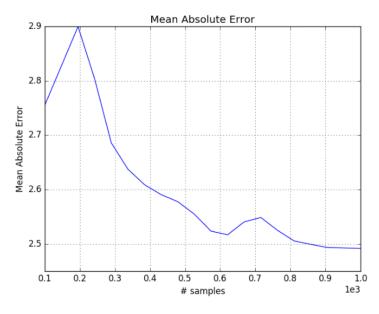


Compute a score (e.g. R²)



Model validation RAVEN scheme

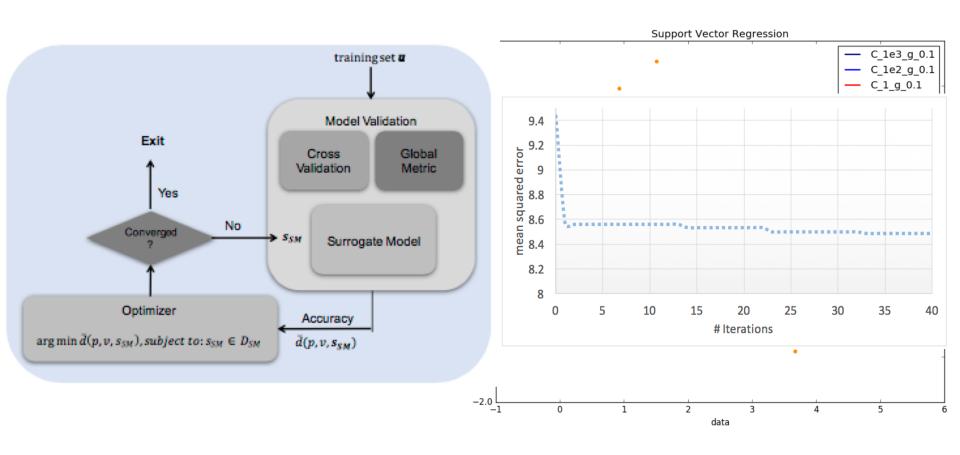




Mean Absolute Error score (Cross-validation) as function of # samples



Surrogate Model Optimization





Ensemble model

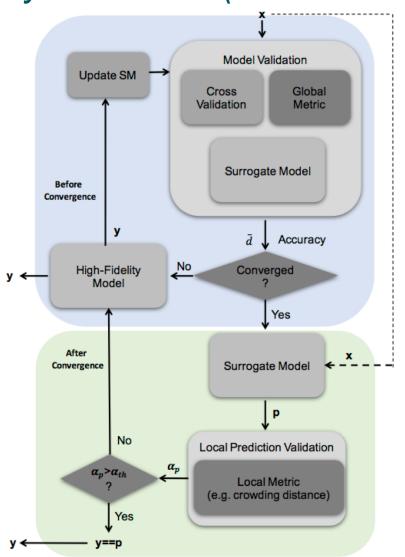
- Multiple "models" can be assembled together and treated as a single one
- Models can be completely heterogeneous (code, external models, ROM)
- RAVEN acts as a hub for the information exchange
- Information passed between "models" could be:
 - Set of lump values
 - Set of time series or fields

$$\overline{x}_{1} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} - \underbrace{\begin{array}{c} \mathbf{Model} \\ \mathbf{1} \end{array}} \Rightarrow \overline{y}_{1} = \begin{pmatrix} \Theta \\ \Sigma \end{pmatrix} - \underbrace{\begin{array}{c} \overline{x}_{2} = \begin{pmatrix} \Phi \\ \Lambda \end{pmatrix}} \Rightarrow \overline{y}_{2} = \begin{pmatrix} \Phi \\ \Pi \end{pmatrix}$$

$$\overline{x}_{3} = \begin{pmatrix} \Theta \\ \mu \end{pmatrix} - \underbrace{\begin{array}{c} \mathbf{Model} \\ \mathbf{N} \end{pmatrix}} \Rightarrow \overline{y}_{3} = \begin{pmatrix} \Psi \\ \Gamma \end{pmatrix}$$



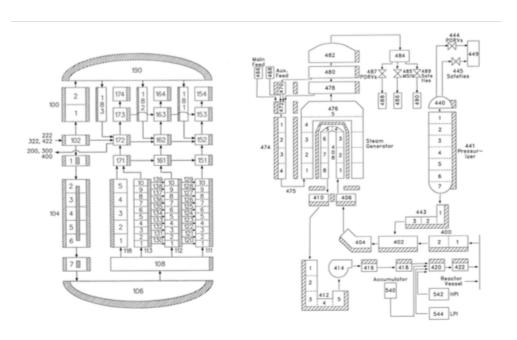
Hybrid-Model (automatic selection ROM/physical model)

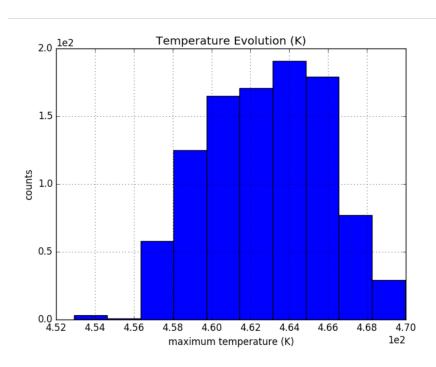


 The HybridModel is designed to combine multiple surrogate models and any other Model (i.e. high-fidelity model) leveraging the EnsembleModel infrastructure, deciding which of the Model needs to be evaluated based on the model validation score.



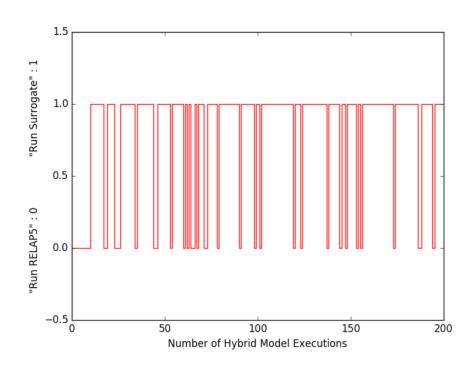
Application of the Hybrid Model on a PWR SBO using RELAP5-3D







Application of the Hybrid Model on a PWR SBO using RELAP5-3D



200 RELAP5 evaluations over 1000 MC Samples

RELAP5-3D

Parameter	Result
mean	462.64
Minimum	458.57
Maximum	467.32
Median	462.64

HYBRID MODEL

Parameter	Result
mean	462.65
Minimum	458.03
Maximum	467.53
Median	462.64



Future work on the Hybrid Model

- Identification of Time-dependent validation metrics
- Extension of the Hybrid Model in the time-domain
- Development of model-based local validation metrics



Thank you