



THE OHIO STATE UNIVERSITY

Surrogate Model Selection in RAVEN for Seismic Dynamic PRA/PSA

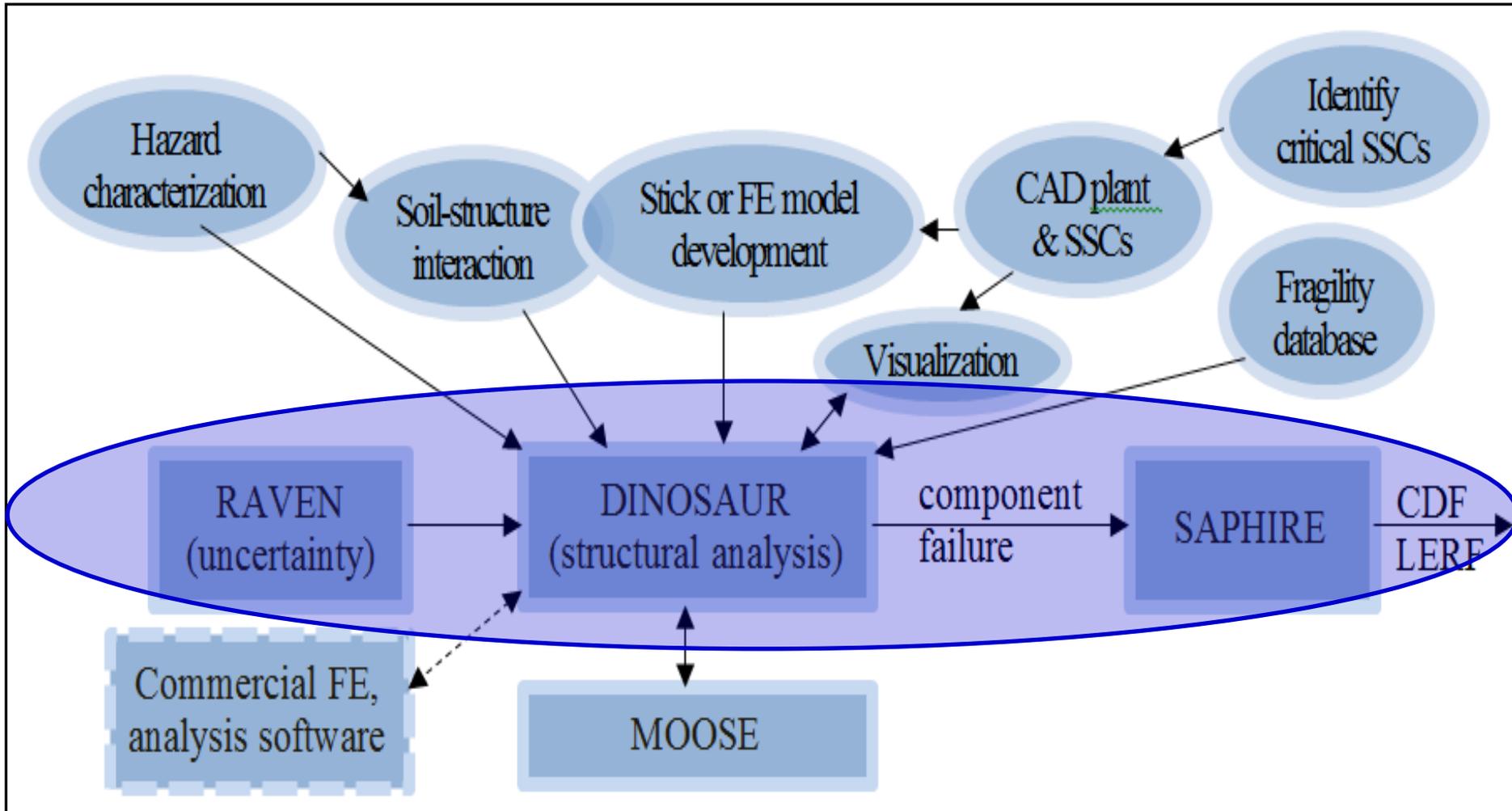
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- The Ohio State University is working to integrate external events analysis with probabilistic risk/safety assessment (PRA) as part of the US DOE Light Water Reactor Sustainability Program
 - The project includes development of advanced tools for uncertainty quantification
- The case study under investigation seeks to:
 - Use surrogate models to reduce the computational burden of uncertainty quantification in seismic PRA
 - Perform sensitivity analyses to determine the limits of applicability of surrogate models
 - Package the efforts within a common computational platform



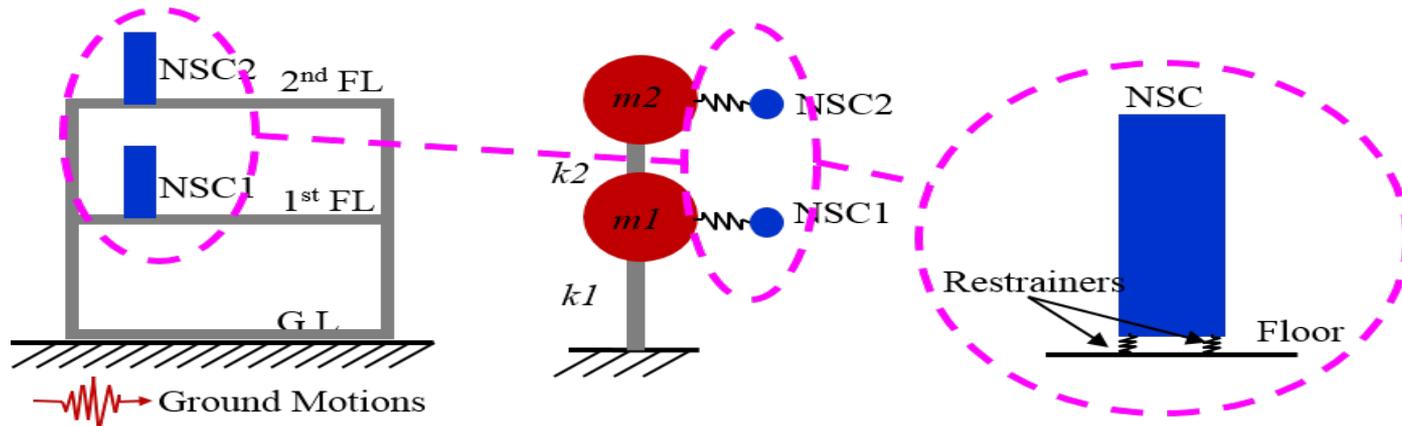
DINOSAUR Module Structure





- Surrogate models have been found to reduce the computer resources necessary for uncertainty quantification.
- The accuracy of surrogate models can vary wildly based on the surrogate model chosen and the scenario.
- The objective of this study is to demonstrate a method to select appropriate surrogate models for a scenario without detailed analysis of the surrogate's construction.
- The study is performed using a stick model to demonstrate the approach.

- Earlier work in this project generated finite element and stick models of auxiliary building
- The seismic response of the stick model was tuned to match the finite element structure in a previous case study (Case Study 1)



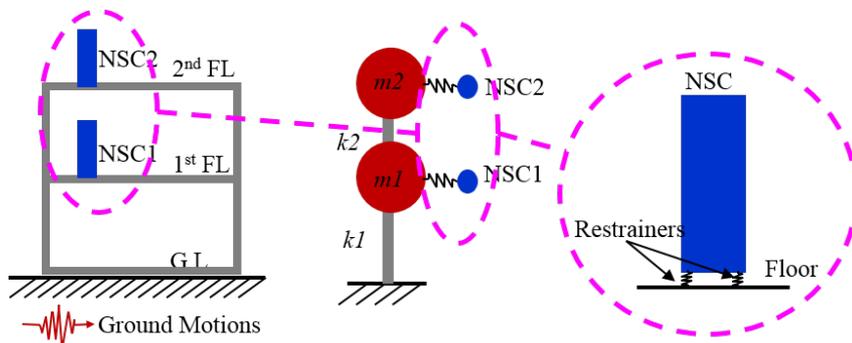


- The objective of Case Study 1 was to perform uncertainty quantification for a typical SPRA configuration.
- The stick model was constructed to approximate the response of an auxiliary building and non-structural components (NSCs) at a nuclear power plant (NPP) at different locations in the auxiliary building.
 - A stick model consists of each floor's mass lumped together in single points, while being joined together by massless sticks with a stiffness equal to that floor's structural stiffness



- Uncertain parameters considered were mass, stiffness and failure acceleration of NSCs.
 - Three subcases involved using a single draw for both floors, a draw per floor from identical distributions or draws from non-identical distributions
- Failure probabilities (including the joint failure probability) were determined for two essentially identical NSCs at two floors of the building.
- A followup analysis determined that training surrogate models could reduce the calculation time.
- Improperly selected surrogate models have a large error.

- Scenario under consideration for this study uses same model as Case Study 1
- Both floors have mass and stiffness drawn from same normal distributions
- Several surrogate models (SGs) are trained on few runs. The errors are then compared to the same SGs trained on a large number of runs.



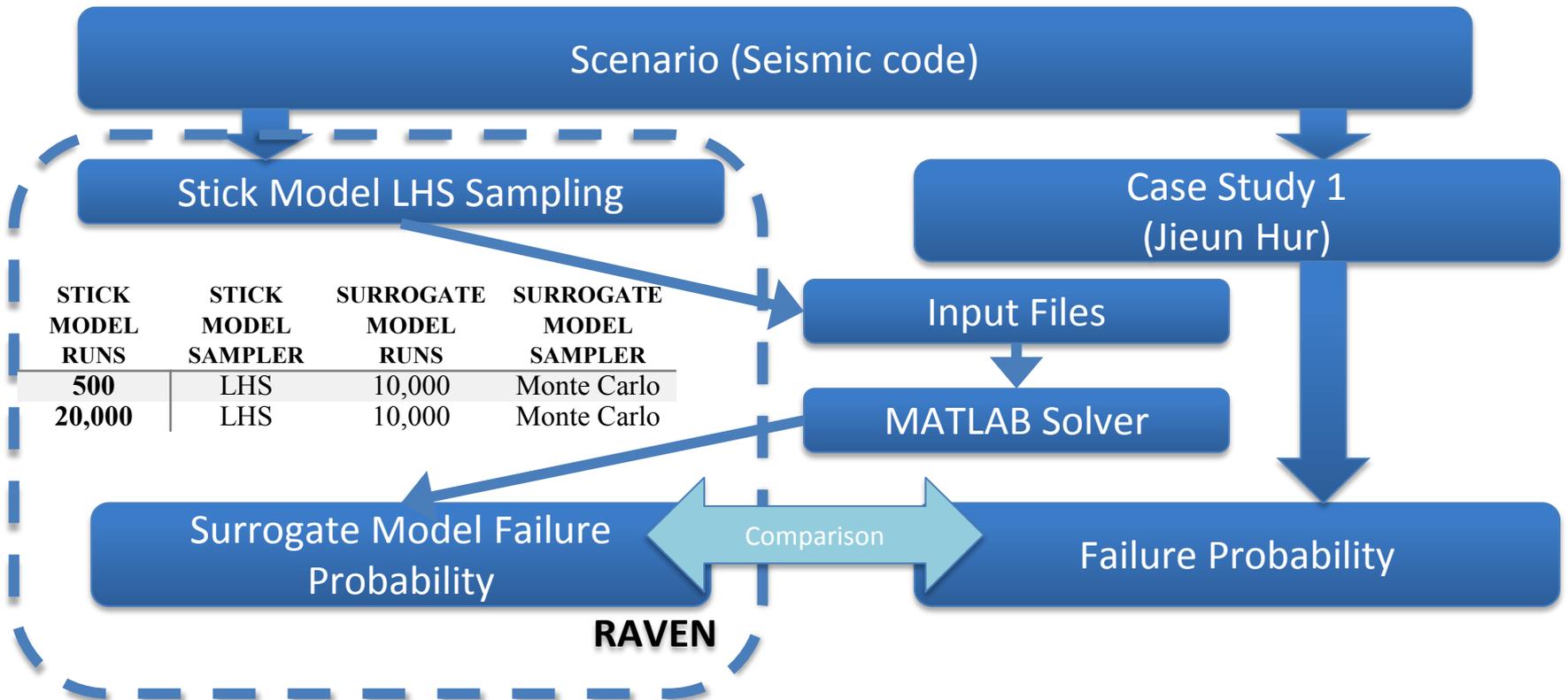
Seismic stick model description

		DISTRIBUTION	MEAN	ST. DEV.
Each floor mass m_1 and m_2 (ton)		Normal	25	2.5
Each floor stiffness k_1 and k_2 (kN/m)		Normal	150,000	15,000
Failure (g)	Acceleration	Log-normal	1.01	0.69

Uncertain parameters for analysis



- SGs are then sampled using previous uncertainty distributions to determine failure probabilities





- SGs are trained using:

$$\Theta(\bar{\theta}_s) \approx \bar{H}(\bar{\theta}_i)$$

- Two types of SGs: Classifiers and Regressors
 - Regressors: Predict the precise figure of merit
 - Classifiers: Convert the figure of merit to success or failures for prediction

$$C_{NSC} = \begin{cases} 0 & \text{if } a_{NSC} < f_{NSC} \\ 1 & \text{if } a_{NSC} \geq f_{NSC} \end{cases}$$



- Eight total SGs were trained

SURROGATE MODEL	SURROGATE TYPE
NEAREST NEIGHBOR	Regressor Model
K=5 NEIGHBORS	Regressor Model
INVERSE DISTANCE WEIGHTING	Regressor Model
NEAREST NEIGHBOR	Classifier Model
K=5 NEIGHBORS	Classifier Model
INVERSE DISTANCE WEIGHTING	Classifier Model
LINEAR SUPPORT VECTOR CLASSIFIER	Classifier Model
C-SUPPORT VECTOR CLASSIFIER	Classifier Model

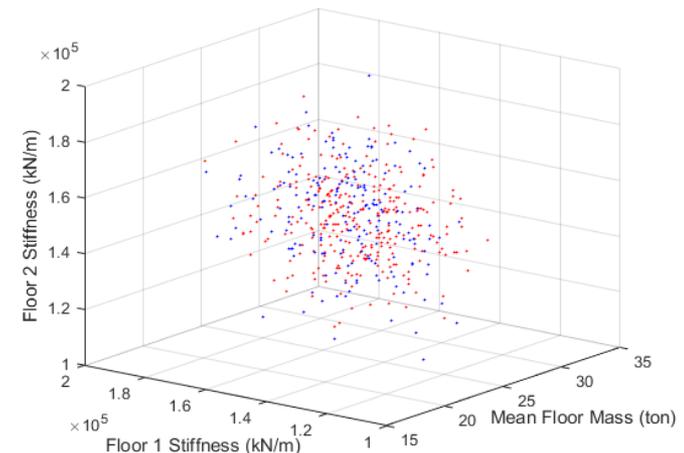
- Nearest Neighbor models poll the nearest K points.
- Inverse Distance Weighting models determine a weighted average.
- Support Vector Classifiers divide the input space into regions of success and failure.



- Stick model analysis shows success or failure cannot divide cleanly into regions of success and failure
- Seismic response is highly driven by structure resonances
- A high-fidelity run was also performed, with similar results

$B_{P1} (NSC_1 GM_S)$	$B_{P2} (NSC_2 GM_S)$	$B_{PJ} (NSC_1 \cap NSC_2 GM_S)$
0.600	0.702	0.600

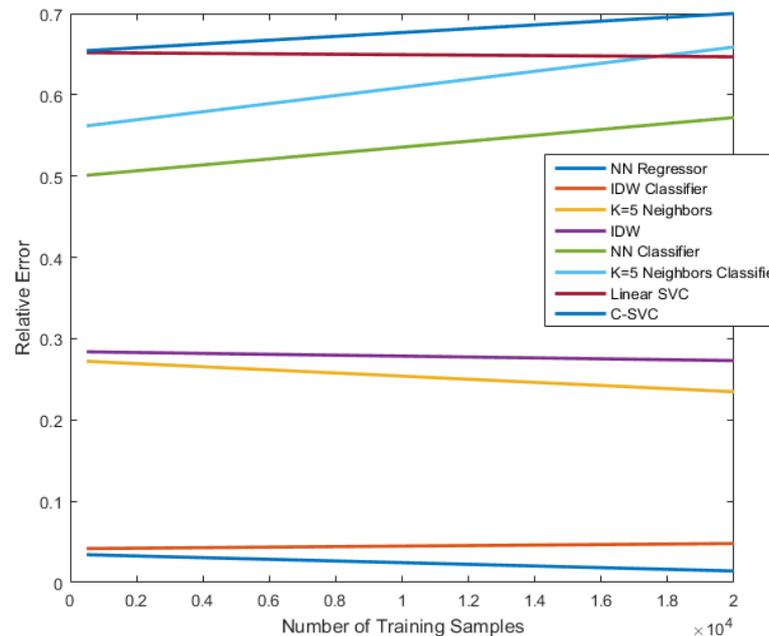
low fidelity model failure probabilities for NSC_1 and NSC_2 .



Input values of the low fidelity seismic stick model and NSC response.



- At both low- and high-fidelity, SGs had similar relative errors.
- Error size did not depend on model type.
- SGs which divide the input space into regions of success and failure had the largest errors.





- Number of runs necessary for uncertainty quantification in SPRA can be large since seismic models with high fidelity have long run times.
- Reduced order SGs can greatly decrease the computing resources needed.
- Large errors may result from SGs if an inappropriate model for the problem under consideration is used.
- The appropriateness of SGs can be determined based on their errors at low fidelity without needing to understand the mathematical basis.



Thank you!



Questions?

Acknowledgement

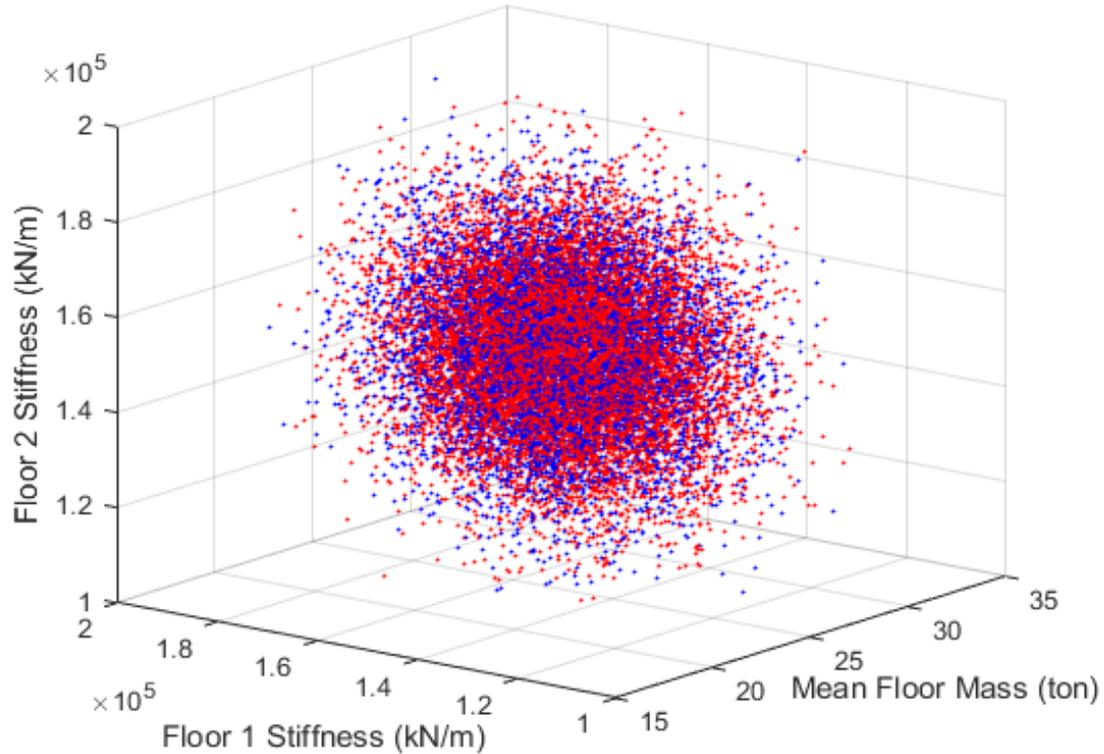
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Input values of the high fidelity seismic stick model and NSC response.