New Methods and Tools to Perform Safety Analysis within RISMC

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INTRODUCTION

The Risk Informed Safety Margins Characterization (RISMC) Pathway under the U.S. Department of Energy Light Water Sustainability Program uses a systematic approach developed to characterize and quantify safety margins of nuclear power plant structures, systems and components. What differentiates the RISMC approach from traditional probabilistic risk assessment (PRA) is the concept of a safety margin. In PRA, a safety metric such as core damage frequency (CDF) is generally estimated using static fault-tree and event-tree models. However, it is not possible to estimate how close we are to physical safety limits (say peak clad temperature) for most accident sequences described in the PRA.

In the RISMC approach, what we want to understand is not just the frequency of an event like core damage, but how close we are (or not) to this event and how we might increase our safety margin through margin management strategies in a Dynamic PRA (DPRA) [1] fashion.

This paper gives an overview of methods that are currently under development at the Idaho National Laboratory (INL) with the scope of advance the current state of the art of dynamic PRA.

TOOLS TO PERFORM DPRA AND UQ

In order to perform DPRA type of analysis, RISMC is relying on a code under development at INL: Reactor Analysis and Virtual Control Environment (RAVEN) [2].

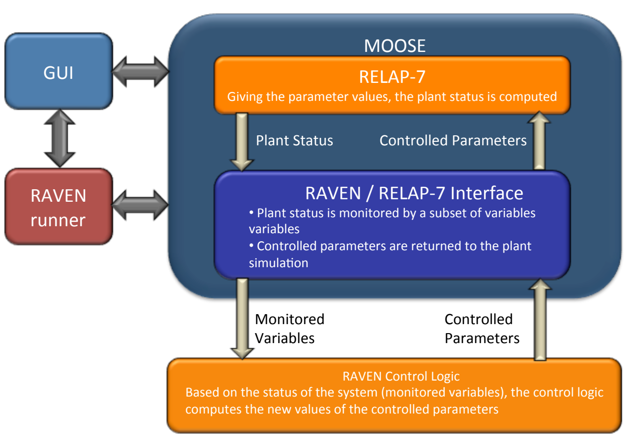

Figure 1. Overview of the RAVEN code [2]

RAVEN (see Fig. 1) is a tool that is able to perform both DPRA and uncertainty propagation (UQ). It is coupled with another code under development (RELAP-7 [3]) using the MOOSE [4] framework. Both DPRA and UQ analysis are controlled by RAVEN that acts as a controller of each RELAP-7 simulation run.

RAVEN has been developed in a modular and pluggable way in order to enable integration of different programming languages (i.e., C++, Python) and coupling with other applications including the ones based on MOOSE. The code consists of four main modules (see Fig. 1):

- RAVEN/RELAP-7 interface
- Python Control Logic
- Python Calculation Driver
- Graphical User Interface

The RAVEN/RELAP-7 interface, coded in C++, is the container of all the tools needed to interact with RELAP-7/MOOSE. It has been designed in order to be general and extendable with different solvers simultaneously in order to allow an easier and faster development of the control logic/PRA capabilities for multi-physics applications. The interface provides all the capabilities to control, monitor, and process the parameters/quantities in order to drive the RELAP-7/MOOSE calculation. In addition, it contains the tools to communicate to the MOOSE input parser whose information, i.e. input syntax, must be received as input in order to run a RAVEN calculation.

The control logic module is used to drive a RAVEN/RELAP-7 calculation. The implementation of the control logic via Python is rather convenient and flexible. The user only needs to know few Python syntax rules in order to build an input. Although this simplicity exists, it will be part of the GUI task to automatize the construction of the control logic scripting in order to minimize user efforts.

The core of PRA analysis is contained in the module called "Raven Runner." It consists in a Python driver in which Monte-Carlo based algorithm has been implemented. It calls RAVEN multiple times, changes initial conditions and seeds the random generator for the distributions (DPRA and UQ). The multiple calculations, required by the employment of these algorithms, can be run in parallel, using queues/sub-process/Python systems.

METHODS TO PREDICT SYSTEM BEHAVIORS

Nuclear simulations are often computationally expensive, time-consuming, and high-dimensional with respect to the number of input parameters. Thus exploring the space of all possible simulation outcomes is infeasible using finite computing resources. However, this is a typical context for performing adaptive sampling where a few observations are obtained from the simulation, a surrogate model is built in order predict behavior of the system (e.g., maximum core temperature), and new samples are selected based on the model constructed (see Fig. 2 top).

The surrogate model is then updated based on the simulation results of the sampled points. In this way, we attempt to gain the most information possible with a small number of carefully selected sample points, limiting the number of expensive trials needed to understand features of the simulation space. From a safety point of view, we are interested in identifying the limit surface (see Fig. 2 bottom), i.e., the boundaries in the simulation space between system failure and system success.

The generic structure of an adaptive sampling algorithm is shown in Fig. 3. Two classes of algorithms have been evaluated and are being implemented within RAVEN:

- Discrete: model generated predicts simulation outcome in a binary fashion, e.g., system failure or system success
- Continuous: model generated predicts an estimate of simulation outcome, e.g., maximum temperature reached in the core

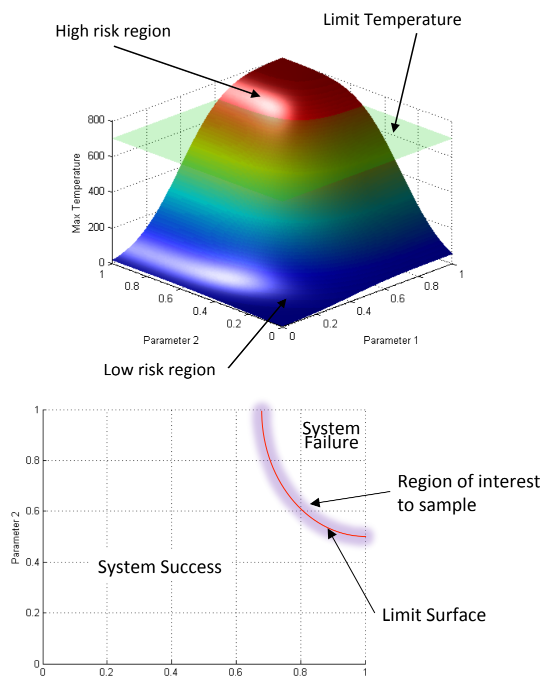

Figure 2. Max core temperature as function of 2 parameters and limit/fail temperature (top) and plot of their intersection: limit surface (bottom)

In the first class, Support Vector Machines (SVMs) have proven to be flexible to model limit surface of an arbitrary shape [5]. The only limitation is that the surrogate model only predicts the simulation outcome in a binary form (failure or success) and does not give any quantitative information of the variables of interest (e.g., max core temperature). Consequently, we then investigate algorithms that can generate continuous reduced order models based on Gaussian Process Models (GPMs).

We the started to evaluate GPM methods (e.g., Kriging method) and then developed more advanced algorithms based on topological constructions of the surrogate model (through Morse-Smale complexes) [6].

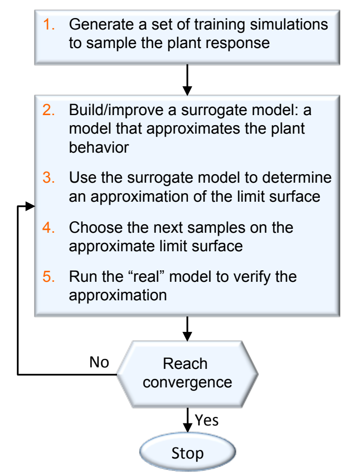

Figure 3. Generic scheme for adaptive sampling algorithms

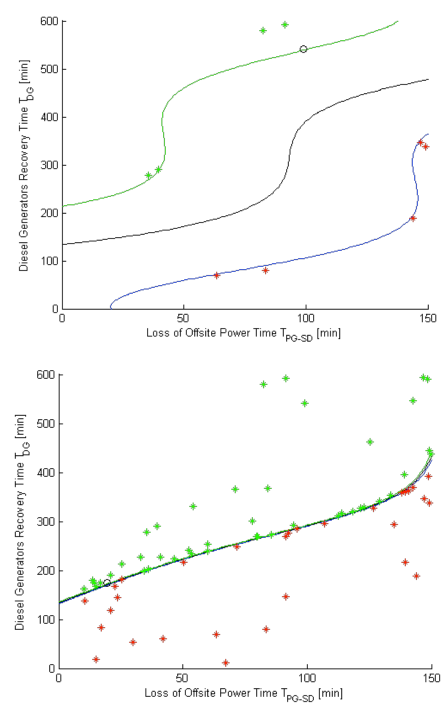

Figure 4. Limit surface obtained for a simplified PWR system for a SBO scenario after 10 (top) and 60 (bottom) samples [5]

These surrogate models are such that they can predict a specific simulation outcome (e.g., max core temperature) . Analogously it would be possible to build a surrogate model that can predict the time at which a certain simulation outcome is reached.

Such prediction capabilities led us to investigate also the possibility to modify adaptive sampling schemes to predict, temporally, the full profile of a simulation given a set of training simulation runs.

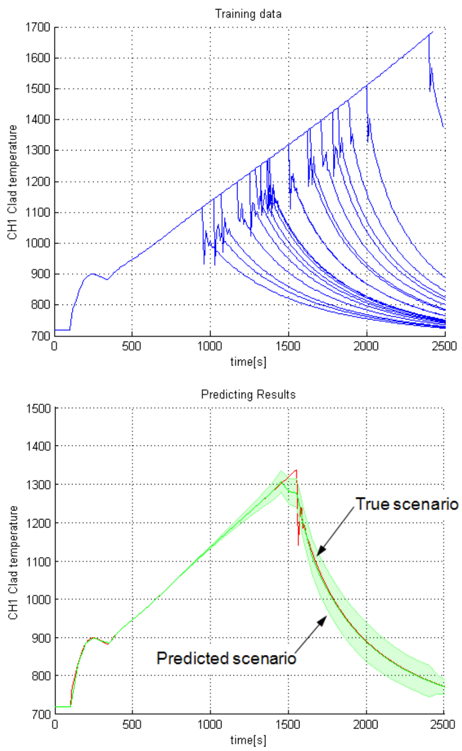

Figure 5. Temporal prediction of simulation runs: training simulations (top) and predicted results (bottom)

Preliminary results shown in Fig. 5 indicate the set of training simulation runs (Fig. 5 top) and predicting results (Fig. 5 bottom). Note that predicted results are displayed in terms of predicted scenario and uncertainties associated to the prediction (light green band around the green line).

METHODS TO GENERATE KNOWLDEDGE FROM DATA

The ability to analyze and identify correlations among timing of events through system dynamics/software/human action interactions is essential for nuclear power plant safety analysis and post-processing of the data generated by DPRA methodologies is still a research topic.

A first approach toward discovering these correlations from data generated by DPRA methodologies has been developed using Fuzzy classification. However, clustering algorithms have allowed users to fully analyze these correlations by considering the complete system dynamics and not only the final outcome [7].

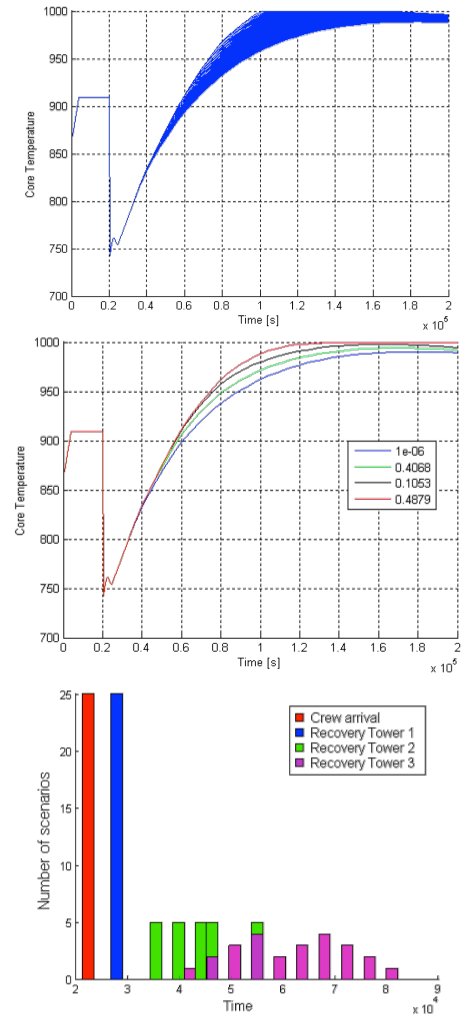

Figure 6. Original data (top), clustered data (middle) and timing of events associated to a cluster (bottom)[7]

Clustering based algorithms can be used to identify groups (i.e., clusters) of scenarios having similar temporal behavior of the state variables. An example [7] is shown in Fig. 6 for a data set generated using ADAPT and RELAP-5 for an aircraft crash initiating event. A plot of all 610 scenarios is shown in Fig. 6 (top); clustering algorithm allowed to identify 4 clusters and the "representative scenarios" for each of these 4 clusters are shown in Fig. 6 (middle). At this point, the analysis can be performed by observing the timing of events that lead to the scenarios contained in that cluster (Fig. 6 bottom).

Moreover, clustering algorithms have proven to assist the user, for example, in the identification of those scenarios having similar temporal behavior but characterized by different outcomes only because the maximum simulation time was passed. In addition, in [7] we showed how clustering algorithms can easily identify outliers scenarios, i.e., scenarios characterized by erroneous/discontinuous temporal behavior due to the fact that the validity boundaries of the code were surpassed.

It may be possible to combine these ideas, the temporal-based adaptive sampling scheme with clustering in order to have a powerful method of "surrogate modeling" that could prove useful for nuclear safety analysis. This idea remains for future investigation.

CONCLUSIONS

The scope of this paper is to give an overview of the tools that RISMC will employ to perform DPRA and UQ analysis for nuclear power plants. We have selected RAVEN as code to perform such analyses for its flexibility to add new algorithms and capabilities. We have also indicated a few R&D paths that we believe will improve such analyses in terms of computational costs reductions and data analysis. We have also indicated how the generation surrogate models may come helpful when we will extend our capabilities for diagnosis and prognosis purposes.

REFERENCES

[1] N. SIU, "Risk assessment for dynamic systems: an overview," *Reliability Engineering and System Safety*, **43**, no. 1, pp. 43-73 (1994).

[2] A. ALFONSI, C. RABITI, D. MANDELLI, J. COGLIATI, and R. KINOSHITA, "Raven as a tool for dynamic probabilistic risk assessment: Software overview," in *Proceeding of M&C2013 International Topical Meeting on Mathematics and Computation,* CD-ROM, American Nuclear Society, LaGrange Park, IL (2013).

[3] D. GASTON, G. HANSEN, S. KADIOGLU, D. A. KNOLL, C. NEWMAN, H. PARK, C. PERMANN, and W. TAITANO, "Parallel multi-physics algorithms and software for computational nuclear engineering," Journal of Physics: Conference Series, 180, 1, 012012 (2009).

[4] D. ANDERS, R. BERRY, D. GASTON, R. MARTINEAU, J. PETERSON, H. ZHANG, H. ZHAO, and L. ZOU, "RELAP-7 Level 2 Milestone Report: Demonstration of a Steady State Single Phase PWR Simulation with RELAP-7," Tech. Rep. INL/EXT-12-25924, Idaho National Laboratory (INL) (2012).

[5] D. MANDELLI and C. SMITH, "Adaptive sampling using support vector machines," in *Proceeding of American Nuclear Society (ANS)*, San Diego (CA), **107**, pp. 736-738 (2012).

[6] D. MALJOVEC, B. WANG, D. MANDELLI, P.-T. BREMER and V. PASCUCCI, "Adaptive Sampling Algorithms for Probabilistic Risk Assessment of Nuclear Simulations," draft for *International Topical Meeting on Probabilistic Safety Assessment and Analysis* (PSA) (2013).

[7] D. MANDELLI, A. YILMAZ, T. ALDEMIR, K. METZROTH and R. DENNING, "Scenario clustering and dynamic probabilistic risk assessment," *Reliability Engineering & System Safety*, **115**, pp. 146-160 (2013).