Comparison of Surrogate Models with Physical Models for Dynamic Probabilistic Risk Analysis Using the RAVEN Code

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INTRODUCTION

Dynamic probabilistic risk analysis (DPRA) [1] has emerged in the nuclear industry as an effective tool to identify points of weakness in nuclear reactors and create a comprehensive approach to quantifying risk. While DPRA allows for detailed analysis, it usually requires thousands of runs due to the necessity of exploring low probability, high consequence events, which can be computationally prohibitively difficult to assess.

Risk **A**nalysis **V**irtual **EN**vironment (RAVEN) [2] is a software package being developed under the Nuclear Energy Advanced Modeling and Simulation program at the Idaho National Laboratory. It is able to manage complex control logic to drive a RELAP-7 [3] simulation and to handle sampling strategies including Monte Carlo, Latin Hypercube, Grid and Adaptive samplers [4].

By performing a thorough investigation of the possibility space of an accident scenario with RELAP-7, RAVEN is able to identify consequences of accident scenarios that have not been encountered [5]. The most computational resource intensive step of a RAVEN analysis is running the RELAP-7 code modeling the physical system behavior. Using surrogate models to represent the outcomes of more complex simulations rather than the full model can greatly reduce the computation effort required.

In situations where the uncertainty distributions of a model are unknown, or when there are multiple sets of uncertainty distributions, DPRA generally requires rerunning the physical model for each set of uncertainty distributions used. By taking an unbiased sample of the physical model and creating a surrogate model from the results, the surrogate model can be sampled under a different set of uncertainty distributions to provide equivalent results. This paper presents an example of this approach.

EXAMPLE SYSTEM AND BASE SCENARIO UNDER CONSIDERATION

A 2-loop pressurized water reactor (PWR) model was created using RELAP-7 based on the Organization for Economic Cooperation and Development (OECD) main steam line break benchmark [6]. Figure 1 shows the physical arrangement of the system under consideration and RELAP-7 model.

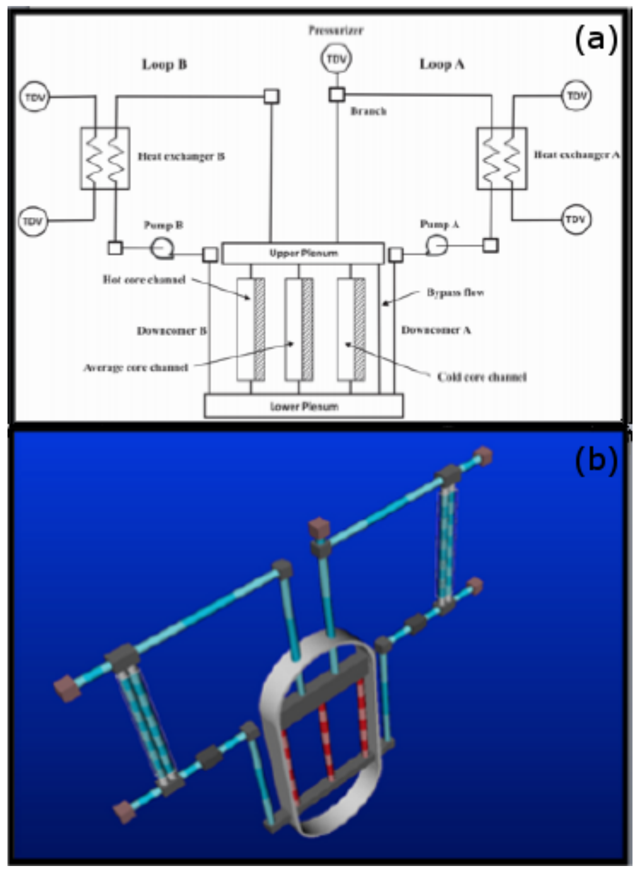


Fig. 1. PWR schematic (a) and RELAP-7 model (b)

For RELAP-7 runs, every fuel pin was classified into one of three groups based on their heat flux, which is modeled as a flow channel with an attached heat structure. Each simplified loop connects from the upper plenum to a steam generator (represented by a heat exchanger) and then through a downcomer to the lower plenum. A single pump model is used in each loop to represent all of the pumping systems (see Fig. 1(b)).

Based on this model, a loss of off-site power (LOOP) event causing a station blackout (SBO) accident was examined. The progression of the accident is that at time *t*=0, outside power is lost, and the plant successfully scrams one second later. At $t=t_1$, the diesel generators fail and the plant enters a SBO condition. This condition persists until AC power is restored, by either repairing the diesel generator systems or recovering off-site power, or the cladding is damaged. Each simulation occurred over a 2500 second period, and in order to force the time of plant failure to fall within that period, the viscosity of the water was artificially altered to reduce the effectiveness of passive cooling systems.

There are four uncertain parameters under consideration:

- *Time of diesel generator failure* t_1 represented by a normal distribution ($\mu = 400\ s, \sigma = 150\ s$)
- *Diesel generator repair time* represented by an exponential distribution ($\lambda = 0.0056/s$) truncated at 1s
- *Time to off-site power recovery* represented by a Weibull distribution ($\alpha = 0.629\ \beta = 1246\ s$)
- *Failure of the cladding* represented by a uniform distribution ($upperbound\ = 1255.3722\ K\ lowerbound = 1699.8167\ K$)

Using this physical model and set of uncertain parameters, a database of results was created. However, the distribution information was not used in the construction of this database. Instead, each parameter was represented by nine grid-sampled points uniformly-spaced in value in order to cover the entirety of the problem space, requiring 9^4=6561 runs. By creating this without considering distribution information, the database is agnostic to the distribution used in analysis. From this database, a surrogate model of the system using an inverse distance weighting scheme [7, 8] to determine success or failure of the cladding. This model was chosen because it has a single tuning parameter. This makes the model as simple as possible at the cost of fidelity.

4000 Monte Carlo runs were performed on the surrogate model, using the distributions above. The same number of runs were performed on the RELAP-7 code, and their probabilities of clad damage were compared.

RESULTS

Between the time of diesel generator failure and the restoration of power, through repair of either offsite power or the generators, the plant is in a SBO condition. During this time, if the coolant recirculation pumps fail to function, the clad temperature rises until the cladding is damaged or power is restored. Figure 2 shows the overlaid temperature profiles of the grid-sampled RELAP-7 runs used in order to create the database of results.

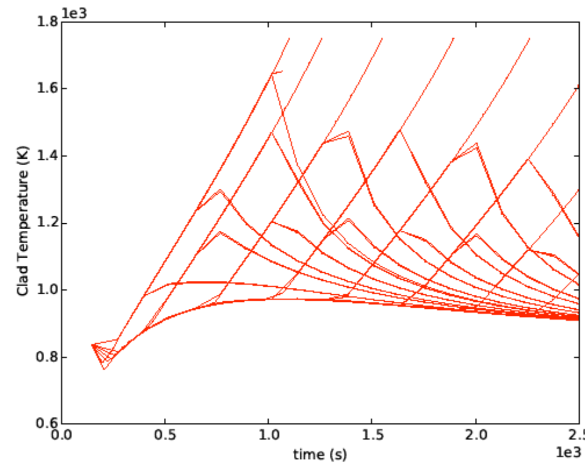
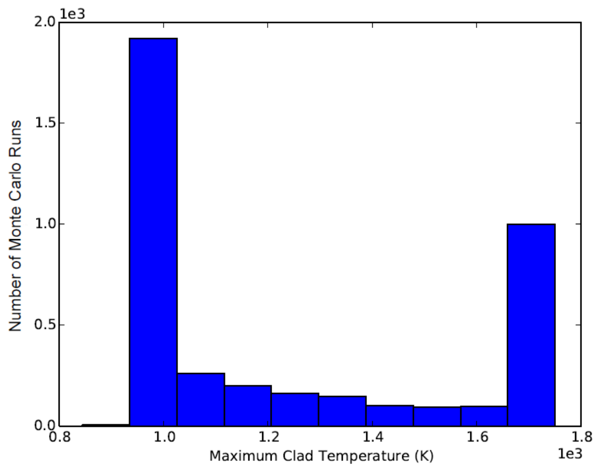


Fig. 2. Temperature of the cladding during grid sampled RELAP-7 runs

In the collection of RELAP-7 runs shown in Figure 2, the temperatures split off from the baseline to rapidly rise at the times where the diesel generators fail. These temperatures continue to increase until the restoration of electric power, where the cladding temperature branches again to cool when water is restored to the core.

From the Monte Carlo sampling performed on the RELAP-7 code, the probability of clad damage was found to be 0.302 ± 0.007, in agreement with the sampling performed on the surrogate model with a probability of clad damage of 0.295 ± 0.007. As the time to perform the sampled runs on the RELAP-7 code was greater than 600 CPU days, while the sampling of the surrogate model could complete in under half a CPU day, there is a large advantage in the necessary computational resources required to determine the probability of Boolean parameters. This advantage is limited to the case when the database of results can be used multiple times, however.

It was also discovered that the accuracy of the surrogate model is limited in scope with respect to the predicted probability of clad damage, which the model was optimized for. The cladding temperature histories shown in Figure 2 follow a limited set of paths, unlike what would be expected from a Monte Carlo strategy. While reducing bias, for continuous parameters this can distort the behavior of a surrogate model.



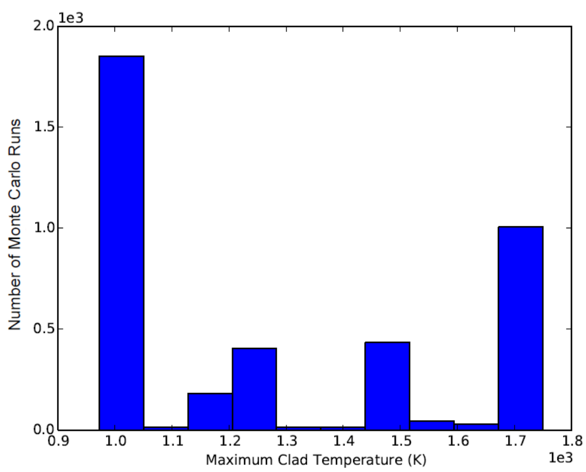


Fig. 3. Maximum temperature histogram of cladding during RELAP-7 (top) and surrogate model (bottom) runs

Between the leftmost part of the graphs in Figure 3, where the plant never enters an SBO condition, and the rightmost part of the graphs, where the simulation was terminated early due to failure of the cladding, an inspection of the graphs shows that there is little agreement. Although the probabilities of cladding damage agree, the surrogate model fails to predict the behavior of the RELAP-7 code in situations where the temperature rises before recovering. Further work remains in the use of surrogate models in the estimation of continuous parameters as opposed to Boolean parameters.

NOMENCLATURE

μ=mean of the normal distribution
σ=standard deviation of the normal distribution
λ= exponential distribution rate parameter
α=Weibull distribution shape parameter
β= Weibull distribution scale parameter

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