Time-Dependent Sensitivity Analysis of OECD Benchmark using BISON and RAVEN

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INTRODUCTION

Developments in uncertainty quantification in nuclear simulations have decreased the computational cost required to perform accurate sensitivity analysis [1, 2, 3, 4]. Implementation of these methods in the RAVEN [5] framework allows additionally for time-dependent sensitivity analysis of uncertain input variables. By demonstration we consider an OECD benchmark case (TODO cite benchmark). We propagate uncertainties in the input parameters using RAVEN operating on the BISON [6] fuels performance code. We then consider the time-evolution of the sensitivity of several output responses to the uncertain input parameters. We perform sensitivity analysis using time-based stochastic collocation for generalized polynomial chaos (SCgPC) and high-dimension model reduction (HDMR) [7].

METHODS

TODO Describe OECD benchmark.

For propagation of uncertainty we make use of the high-dimension model reduction (HDMR) expansion,

$$u(Y) = u_0 + \sum_{n=1}^{N} u_1 + \sum_{n_1=1}^{N}\sum_{n_2=1}^{n_1-1} u_{n_1,n_2} + \cdots, \tag{1}$$

where $u(Y)$ is the response as a function of inputs $Y = (y_1, \ldots, y_N)$, N is the dimensionality of the input space, and the components u_i are defined as

$$u_0 \equiv \int \cdots \int u(Y) dY, \tag{2}$$

$$u_1 \equiv \int \cdots \int u(Y) dy_2 \cdots dy_N, \tag{3}$$

$$u_{1,2} \equiv \int \cdots \int u(Y) dy_3 \cdots dy_N, \tag{4}$$

and so forth. Each of the terms in Eq. 1 can be represented using a generalized polynomial chaos expansion,

$$u(Y) \approx \sum_{k \in \Lambda} c_k \Phi_k(Y), \tag{5}$$

where Φ_k are multidimensional polynomials of order $k = (k_1, \ldots, k_N)$ and Λ is a combination of multi-indices corresponding to polynomial orders. Scalar coefficients c_k are approximated using sparse-grid collation numerical integration citesmolyak.

RESULTS

In Figures 1-5, the evolution of sensitivities of the various responses are shown with respect to increasing burnup. In addition, the power history used in the simulation is overlayed to provide insight in time-based changes. In each case, only the most significant uncertain inputs are shown for clarity.

For both the max clad surface temperature and max fuel centerline temperature, one parameter (inlet temperature and fuel conductivity respectively) dominates variance over most of the history; however, system power is more impactful near gradients in the power profile.

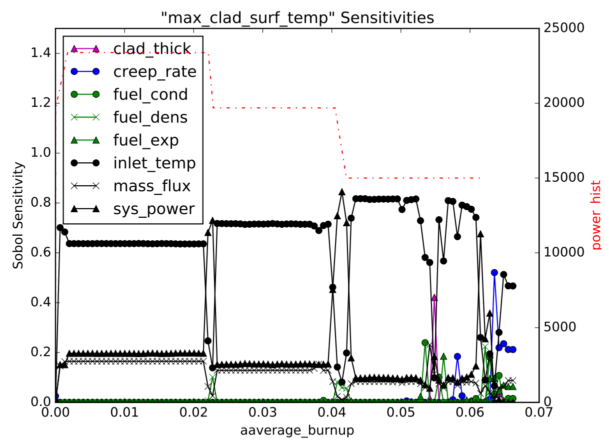

Fig. 1: Max Clad Surface Temperature

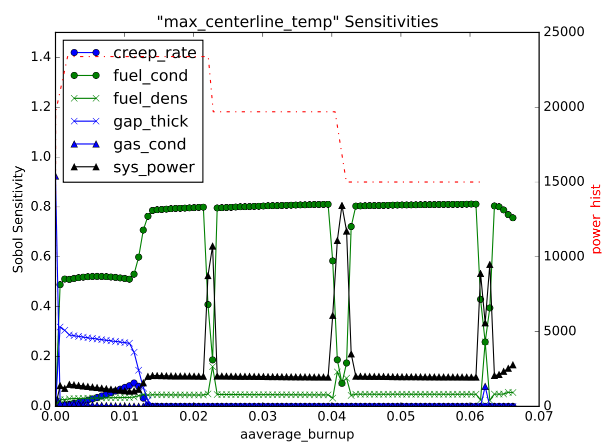

Fig. 2: Max Fuel Centerline Temperature

As expected, the clad creep rate is the most sensitive parameter for clad creep strain; however, it is interesting to note the rise and fall of the gap thickness as an important parameter in the middle of the burnup range.

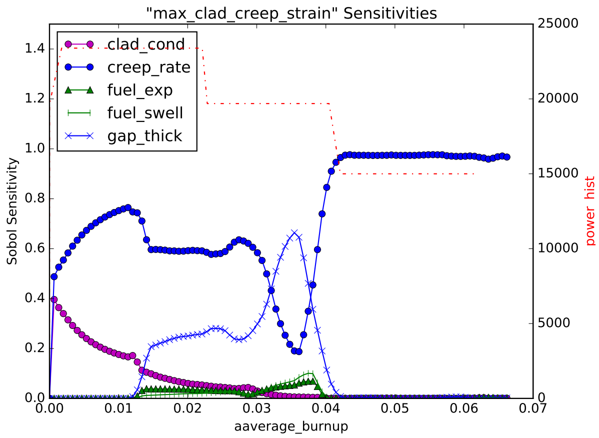

Fig. 3: Max Clad Creep Strain

Early in life the fission gas release is dependent on several parameters, which gives way to only the fuel conductivity and system power later.

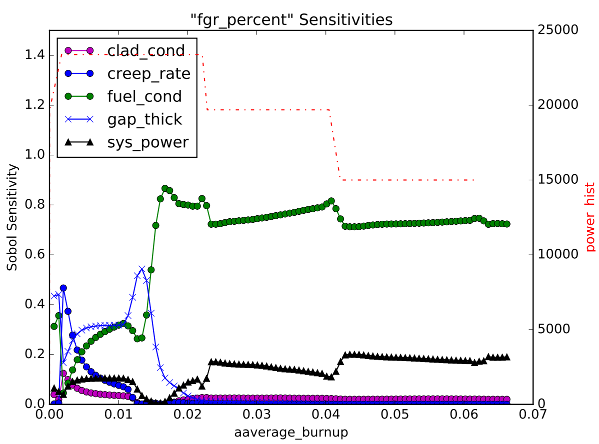

Fig. 4: Fission Gas Release (Percent)

The sensitivities in the variance of clad elongation have three distinct sections. At the beginning, clad elongation is perturbed most by clad conductivity, inlet temperature, and system power, with growing influence from fuel density. These are somewhat suddenly replaced by gap thickness, which then slowly trades places with clad creep rate over the remainder of the life cycle.

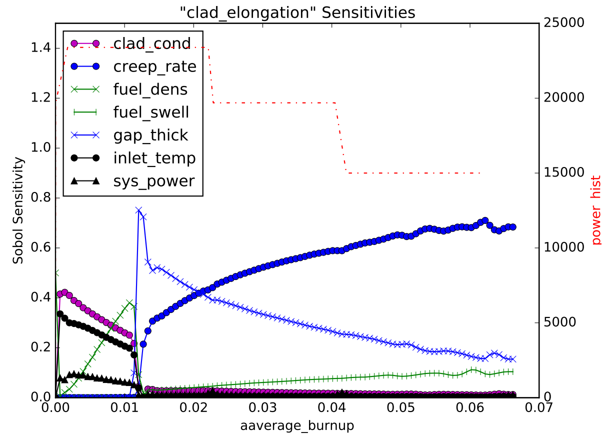

Fig. 5: Clad Elongation

DISCUSSION

We have demonstrated how HDMR and SCgPC can be used in RAVEN to perform time-dependent uncertainty propagation analysis in codes modeling transient behavior. Reviewing the time-evolution of Sobol sensitivities provides new methods in understanding the impact of uncertain input parameters as changes occur during the transient simulation. At small additional cost to static uncertainty propagation, transient analysis has valuable insights to offer.

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