

# Rethinking Sensitivity Analysis of Nuclear Simulations with Topology

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## ABSTRACT

In nuclear engineering, understanding the safety margins of the nuclear reactor via simulations is arguably of paramount importance in predicting and preventing nuclear accidents. It is therefore crucial to perform sensitivity analysis to understand how changes in the model inputs affect the outputs. Modern nuclear simulation tools rely on numerical representations of the sensitivity information – inherently lacking in visual encodings – offering limited effectiveness in communicating and exploring the generated data. In this paper, we design a framework for sensitivity analysis and visualization of multidimensional nuclear simulation data using partition-based, topology-inspired regression models and report on its efficacy. We rely on the established Morse-Smale regression technique, which allows us to partition the domain into monotonic regions where easily interpretable linear models can be used to assess the influence of inputs on the output variability. The underlying computation is augmented with an intuitive and interactive visual design to effectively communicate sensitivity information to nuclear scientists. Our framework is being deployed into the multipurpose probabilistic risk assessment and uncertainty quantification framework RAVEN (Reactor Analysis and Virtual Control Environment). We evaluate our framework using a simulation dataset studying nuclear fuel performance.

**Keywords:** Sensitivity analysis, uncertainty, nuclear simulation, computational topology.

## 1 INTRODUCTION

Nuclear fuel performance behavior is a very complex and multi-physical phenomenon that is, nonetheless, crucial in determining both the economical and safety performance of a nuclear power plant. Since the 2011 nuclear accident in Fukushima, Japan, significant research has been focused on improving the simulation capability of fuel behavior to design safer (i.e., accident-tolerant) fuel. Qualification of a new fuel design is a long process lasting for years and costing billions of dollars. It is therefore natural to try to improve this process by increasing the understanding of the new fuel design behavior via sensitivity analysis (e.g., [32, 40]) before starting any physical experiment phase.

Given the large span of phenomena impacting fuel performance, engineers are tasked with finding the optimal design in a multidimensional simulation space where the system behavior is potentially nonlinear. Sensitivity analysis via regression has historically been used to guide engineers in the optimization process and in identifying the leading phenomena. However, using a simple linear regression model in *global* sensitivity analysis may fail to capture intrinsic local behaviors when the system is highly nonlinear. For this reason, we perform *local* sensitivity analysis and visualization

of multidimensional nuclear simulation data using partition-based regression models. We use Morse-Smale regression (MSR) [26] to identify regions of approximate monotonic behavior within the system response and perform regression and sensitivity analysis locally on these regions.

HDViz [25] uses the same domain partitioning as MSR. Our collaborating scientists have previous exposure to HDViz in risk assessment of nuclear datasets [35, 36]. The scientists found merit in HDViz’s ability to provide a meaningful partitioning amenable to SA, however the system’s complexity made it difficult to isolate the desired local SA information. As such, we seek to provide a more targeted representation of the data for performing SA.

Combining domain decomposition with local regression on the analysis side provides us the opportunity to create more targeted and detailed visual encodings than a global approach. Through close interactions with nuclear scientists, the visual encodings are designed with specific requirements in mind, and we aim to keep each view as simple as possible to enhance its usability. We follow the core design study stages [46]—discover, design, implement, and deploy—in this application-driven research and highlight our contributions:

- We use the established Morse-Smale regression [26] in the context of sensitivity analysis, together with other common sensitivity metrics, to represent the main drivers within local regions of the model domain. Such a representation leads to a unique set of visualization design requirements.
- We report on the iterative process of refining and extending an existing visualization tool, HDViz [25], to match the needs of nuclear scientists. We report on the successful integration of our framework into the workflow of RAVEN [42], a multi-purpose risk assessment and uncertainty quantification software in nuclear engineering.

Our system targets structured/unstructured point cloud data of up to tens of dimensions. We validate and reflect on the efficacy of the new design using a 3D dataset from nuclear fuel analysis. Our goal in this analysis is to understand the effects of different fuel parameters on the stress of the fuel cladding. Excessive stress can lead to cracks in the cladding contaminating the plant environment.

## 2 RELATED WORK

Our proposed technique focuses on performing sensitivity analysis and visualization for multidimensional nuclear simulation datasets modeled as scalar functions observed on sampled data. We employ a domain partitioning of the model, followed by local regression and analysis within each partition, and provide intuitive visualization for nuclear scientists. We review the most relevant related work on partition-based regression, sensitivity analysis methods, and visualization systems designed for sensitivity analysis.

**Partition-based regression.** Partition-based regression techniques typically employ a systematic domain partitioning based on certain criteria, coupled with regression models fitted to each partition, to identify and understand local structures of the model. They can be classified based on their partitioning criteria: those seeking to minimize numerical errors [2, 7, 11, 13, 22] and those based on geometric analysis [26, 33]. In particular, regression trees are constructed by recursively partitioning the domain into multiple partitions at *optimal* locations in the domain (where the optimal criteria can vary), and each partition is fitted with constant [7],

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linear [2], low-order splines [22], or polynomials [11]. On the other hand, Principal Hessian direction (PHD) tree regression [33] splits the domain into areas of high curvature.

We employ the established MSR technique [26], which, being geometrically motivated, is similar to the PHD approach. MSR utilizes a domain partitioning induced by the Morse-Smale complex (MSC) of the regression surface. The MSC partitions the domain into monotonic regions, and MSR takes advantage of the monotonicity implied by this partitioning and builds linear models to fit each partition to capture local interactions between input and output parameters. The MSC is at the core of the successful HDViz system [25]. HDViz and its extension have been previously applied in nuclear engineering [34, 35, 36]. However, the insights of nuclear scientists are limited by the complexity and the lack of intuition provided in the original visualization. In this paper, we follow an iterative process of designing and refining a new visualization system, using HDViz as a basis, that specifically targets nuclear scientists as end users and sensitivity analysis as the end task. We collaborate closely with nuclear scientists throughout the discover, design, implement, and deploy stages; and we document such an effort in Section 4.

**Sensitivity analysis methods.** Sensitivity analysis (SA) studies how changes in the model inputs affect the outputs; see [45] for a survey. SA approaches can be categorized into local SA and global SA. *Local* SA addresses sensitivity relative to point estimates of the parameter values, whereas *global* SA focuses on information for the entire parameter distribution [29]. Local SA studies the change of model response by varying one parameter while keeping other parameters fixed. A common approach, differential SA, computes the location-dependent partial derivative of the output with respect to an input parameter. Global SA, on the other hand, explores the change of model response by varying all parameters simultaneously. Common global SA approaches include generalized SA [31] and those based on the design of experiments.

Contemporarily available SA methods include correlation analysis [49], regression analysis [23], Sobol sensitivity indices [48], Morris one-at-a-time screening (MOAT) [38], Gaussian process (GP) screening [43], multivariate adaptive regression splines (MARS) screening [22], etc.; see [24] for a comprehensive evaluation. For example, correlation analysis measures parameter sensitivity by correlation coefficients, such as the Pearson correlation coefficient (PEAR) and Spearman rank correlation coefficient (SPEAR), which measure the strength of a linear (or monotonic) relationship between model parameters and model responses [24]. Regression analysis involves fitting a linear regression to the model response and using standardized regression coefficients to evaluate parameter sensitivity. MARS and GP screenings are both examples of response surface methods used to derive relative scores of the overall effects of the parameters [24]. For a survey on SA methods in the field of nuclear engineering specifically, see [1].

Our analysis based on MSR falls somewhere between a local SA and a global SA approach. It is a variation on traditional regression analysis, as it employs topology-inspired partition-based regression models. MSR allows us to partition the domain into regions of uniform gradient flow such that a linear model is fitted within each partition. We rely on first derivative information and the fitness of our local models, and also provide the option to compute PEAR, SPEAR, and canonical correlation analysis (CCA) coefficients. The objective of this paper is not the choice of superior statistic in SA, but rather the use of topology to provide more meaningful domain partitioning to support SA.

**Sensitivity analysis and visualization.** We give a brief review of several visualization systems designed for SA, in particular, systems that enable visual exploration of local sensitivity information. HDViz [25] characterizes the behavior of system outputs with respect to input parameters geometrically. HyperMoVal [41] uses support vector regression (SVR) [47] for high-dimensional data and visually

validates a model against the ground truth. It highlights discrepancies between the data and the model and computes sensitivity information on the model. We provide similar capabilities in our system to report on the fitness of our regression model per partition. Berger et al. [4] utilize both nearest neighbor regression and SVR to create a visual interface geared toward optimizing performance in car engine design, where the software displays local sensitivity information on and near a user-selected focal point. Vismon [5] provides SA to the visualization of the uncertainty of a simulation for fisheries scientists.

Canonical correlation analysis (CCA) has been used in the heliograph [18] and Slycat [16] systems to determine correlations between multiple inputs and multiple outputs in a global setting for ensemble data. Other related works visualize local sensitivity information by encoding partial derivative, using glyphs [27], scatterplots [9, 10], and histograms [3].

Our method is, in spirit, similar to systems provided in May et al. [37] and Muhlbacher et al. [39], by providing the capabilities to interactively refine the partitioning during the SA to give a multi-scale view of the sensitivity information. However, data is partitioned along one or two dimensions (i.e., input parameters) in both cases whereas our partitioning spans all dimensions. We differentiate ourselves from HDViz: First, we rethink SA of nuclear datasets, e.g., using regression coefficients derived from topological partitions, which is not the focus of the original HDViz framework. Second, we report on a design study process targeting nuclear scientists to develop effective tools to be integrated into RAVEN.

### 3 TECHNICAL BACKGROUND

**Morse-Smale regression and Morse-Smale complex.** We apply Morse-Smale regression (MSR) [26] in the context of SA. MSR builds upon a domain partitioning of a dataset induced by the Morse-Smale complex (MSC) and employs a linear regression fit within each partition, thereby exploiting its monotonicity. The MSC itself has been successfully utilized in visual exploration of simulation data modeled as high-dimensional scalar functions [25, 34, 35, 36]. Fig. 1a shows the MSC of a 2D test function with four maxima and nine minima. The MSC decomposes the domain into 16 partitions such that each partition can be well approximated by a linear model as shown in Fig. 1b.

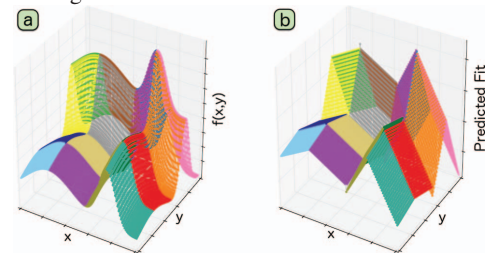


Figure 1: (a) MSC of a 2D height function that induces a partitioning of the domain. (b) Linear models are fit to each partition.

The topological characteristics of the MSC are at the core of MSR. Here, we give a high-level description; see [20] for details. The MSC partitions the domain of a scalar function into monotonic regions, where points in each region have gradient flow that begins at the same local minimum and ends at the same local maximum of the function. Furthermore, the MSC can be simplified based on the notion of *topological persistence* [19, 21]. For a fixed scale, the main idea behind the simplification is to merge its corresponding partitions based on a measure of their significance (i.e., persistence); see Fig. 1d-e of [35] for an example applied to the MSC.

For point cloud data, the MSC can be approximated [12, 25], enabling MSR to be applied in high dimensions. Points are connected by neighborhood graphs such as the  $k$ -nearest neighbor (kNN) graph, and gradients are estimated along the edges of the graph. In our context, we utilize similar approximation schemes [25, 26], where

points are connected using the relaxed Gabriel graph, which was shown to give superior results in extracting topological features [15] compared to the kNN graph.

**Linear regression and sensitivity analysis.** For our analysis, we use *least square linear regression* to fit each partition. To obtain the coefficient estimates, such a least-squares fitting minimizes the sum of squared residuals. For a given partition with  $n$  data points, let  $y = [y_1, \dots, y_n]^T$  be the  $n$ -by-1 vector of observed response values,  $X$  be the  $n$ -by- $m$  design matrix of the model (that is,  $X_{ij}$  is the  $j$ -th dimension of the  $i$ -th data point), and  $\beta$  be the  $m$ -by-1 vector of coefficients. We minimize the error estimate:  $s(\beta) = \sum_{i=1}^n (y_i - \sum_{j=1}^m X_{ij}\beta_j)^2$ . In matrix form, we obtain the coefficient estimates  $\hat{\beta}$  in the following way:  $\hat{\beta} = \arg \min_{\beta} s(\beta) = (X^T X)^{-1} X^T y$ . For SA, we use the regression coefficient  $\hat{\beta}_i$  ( $1 \leq i \leq m$ ) to evaluate the sensitivity of the  $i$ -th dimension.

**Coefficient of determination.** For a given partition fitted with a linear regression model, it is important to evaluate how well the data points fit the model by computing the *coefficient of determination*, or the  $R^2$  score. Given a partition with  $n$  data points, for the  $i$ -th data point,  $y_i$  is the observed response value and  $\hat{y}_i = \sum_{j=1}^m X_{ij}\beta_j$  is the fitted response value. Let  $\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$  be the mean of the observed response values. The *coefficient of determination* is computed as  $R^2 = 1 - \sum_{i=1}^n (y_i - \hat{y}_i)^2 / \sum_{i=1}^n (y_i - \bar{y})^2$ .

We extend such a notion by ranking and considering *how many* input dimensions are sufficient to provide an optimal fit. We select a subset of input dimensions for the  $n$  data points, apply least square linear regression on these points with reduced dimensions, and evaluate the  $R^2$  score of the linear fit. The closer the value of  $R^2$  is to 1, the better the linear regression fits the data with the selected subset of input dimensions.

#### 4 PROBLEM CHARACTERIZATION AND ABSTRACTION

We follow the core stages of a design study [46], namely, discover, design, implement, and deploy, in our application-driven research. During the *discover* stage, we focus on problem characterization and abstraction. We learn the targeted domain of study (in this case, SA for nuclear simulations) through close interactions with nuclear scientists. In this process, we study their *existing work flow* and *design requirements* to better enable knowledge discovery via analysis and visualization.

**Existing workflow.** Before designing our visualization solution, we actively engage nuclear scientists to understand their domain problems and the existing workflow (i.e., their common practices) in SA. As a first approximation, the scientists typically perform a global SA via linear regression or correlation analysis. Point-wise SA is used to estimate gradient information at specific locations via back-of-envelope computation, or a reduced order model (ROM) is constructed from experimental data whereupon statistical information can be collected. The scientists would also manually divide the data domain into subregions that exhibit changes in gradient behavior based on axis-aligned scatterplot projections; then global SA that combines resampling and ROM construction is applied to each manually extracted subregion.

During the discover stage, we help the nuclear scientists formulate and examine their data analysis and visualization needs through an iterative process, where we listen to their description of domain problems, characterize and abstract their problems into design requirements, and obtain feedback regarding abstractions for continuous refinement. We identify several challenges in the existing workflow that are summarized into the following design requirements:

**A: Structure-based domain partitioning amenable to local SA.** As suggested by Gerber et al. [26], we first considered numerous forms of partition-based regression that can be applied for local SA. However, most of these are based on greedy, local operations focusing on optimizing some quality metric. Since the task of our

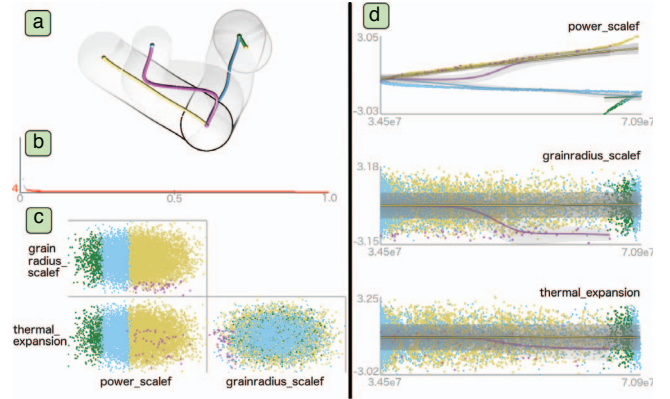


Figure 2: HDViz applied to the nuclear fuel dataset described in Section 7. (a) Topological skeleton: each summary curve in the visual space corresponds to a partition of the data; transparent tubes capture the spread (width) and density (luminance) of the partition. (b) Persistence chart: number of partitions plotted as a function of scale. (c) Scatterplot matrix of partitioned data. (d) Inverse coordinate plots: summary curves and partitioned data are projected onto a 2D plot where the x-axis represents the output dimension, and each y-axis represents an input dimension.

collaborators was understanding trends occurring in the data rather than accurately (potentially overfitting) the data, we selected MSR, as it considers the global structure of the data.

In fact, MSR is particularly suited to this task as each partition is assumed monotonic and thus well described by a simple set of simple sensitivity coefficients. In addition, its flexibility and robustness to noise allow it to be used in an exploratory task such as SA. Existing local SA is restricted to be point-wise, and domain partitioning is done manually via a time-consuming process; while our proposed SA, built upon MSR, applies automatically and efficiently to partitions at multiple scales. Using HDViz as a starting point (see Fig. 2), it is an ongoing process for us to define new visual design requirements as well as refine existing ones that satisfy the various SA tasks.

**B: Intuitive visualization of data hierarchy.** Existing visualization using HDViz has a very steep learning curve for data practitioners in general, is particularly nonintuitive for nuclear scientists, and has very limited support for the SA pipeline. For example, when presented with the topological skeleton seen in Fig. 2, nuclear scientists have questioned the meaning and utility of the oscillations produced by the inverse regression and the geometric interpretation of their 2D projection. During our contextual inquiries [30], we notice that the scientists typically disable the transparent tubes surrounding the inverse regression curves (Fig. 2a). Further interactions reveal that the density and geometry information provided is considered “distracting” and uninformative in their context. Instead, the scientists use the topological tube view to count the number of partitions and extrema at various scales.

Selecting the “appropriate” scale (i.e., persistence level) from the persistence chart remains an unintuitive process when the scientists are rarely aware of how many “noisy” features exist in the data. We have expended effort designing various ways to convey such information to the users, as evidenced in Section 5. Understanding how the scientists interact with the topological view has greatly influenced its design in our iterative process. We understand that the scientists are primarily interested in a high-level picture of their data; therefore, we simplify our visualization to an abstract 2D representation that enables easier selection and manipulation of partitions and supports well-integrated, interactive selection of scales. Finally, the new visual representations should convey information about different scales within the data hierarchy, but also provide context about the partitions within a fixed scale. The topology map

described in Section 5 is designed to fulfill such requirements.

**C: Integration of common practices with new designs.** We incorporate visual tools that are familiar to the nuclear scientists (e.g., scatterplots) into our new visual design to ease the knowledge discovery process. For example, the scientists could select a MSC-based partition and observe its associated point cloud clustered in a geometrically coherent space in the corresponding scatterplot. Such an integration gives the users some intuition of how the topological partitioning is being performed. In addition, the scientists find that the scatterplots also provide some sense of data density within each partition – such information is vital to the users as it is directly related to the confidence associated with the derived sensitivity information. Knowing such details also allows us to encode density information into other representations not prone to the occlusion problem.

**D: Presentation of comparative and quantitative information.** Initial visualizations of the sensitivity information focus on a comparative analysis that uses shapes of different sizes to convey differences among individual partitions in the data. Though it is useful for quickly detecting major trends, the scientists have requested the numeric measurements of each partition to be displayed as this information is more familiar to them and gives them the increased amount of accuracy necessary for decision-making. Additional designs have been suggested (such as the fitness view detailed in Section 5) by the scientists that allow us to better understand their mental model of the data and design our visualization accordingly.

**E: Scalable analysis and visualization.** The existing SA capabilities do not scale well with the increasing number of parameters/dimensions, but our proposed SA using MSR scales well in high dimensions. Given point cloud data, the analysis in [26] has shown that the algorithm in [25] provides a good approximation of the true MSC of the underlying (unknown) function when the smallest feature (signal) of  $f$  has a persistence that is an order of magnitude larger than the standard deviation of the noise. The running time of the MSC does not depend on the ambient dimension of data points, but rather the topological complexity (e.g., number of local extrema) of the underlying function. Therefore, we employ a typical assumption on our targeted datasets such that they have moderate topological complexity, and their topological features can be well approximated. In addition, we require that the new visual design remains intuitive and informative even with increasing dimensionality. Scalable visualization is discussed in Section 5A.

## 5 VISUALIZATION DESIGN

In the *design* stage, we focus on data abstraction, visual encoding, and interaction mechanisms [46]. We have proposed multiple visual encodings where the feedback from nuclear scientists helps us narrow them down to a few usable solutions. These solutions are integrated into a linked view system with multiple visual components providing interactive functionalities, as illustrated in Fig. 3.

A typical workflow begins with the *topology map*, where a user can navigate through partitionings at different scales, and at a chosen scale, explore the structure of the partitions. Within this view, one can understand at a glance the number of local extrema for a given partitioning, their relative importance encoded by persistence, and their connectivity. The appropriate choice of scale is then validated by the *persistence diagram* [14] and the *barcode* [8]. At a fixed scale, the user then selects a subset of partitions for further SA. 2D or 3D scatterplots can be constructed for selected partitions by choosing any two or three input/output dimensions, where the output dimensions include both observed and predicted values. Subsequently, the user can choose to build a *histogram* of any chosen input/output dimension. Such a histogram can also be used for selecting and filtering data for further analysis. Finally, sensitivity information is computed when requested and then visualized on a per dimension basis using the *sensitivity view*, and linear fitness information in terms of  $R^2$  score is given in the *fitness view*. We give a detailed

description of the *primary* visual encodings below: topology map, scatterplot projection, sensitivity view, and fitness view; followed by a brief introduction to the *secondary* visual encodings: persistence diagram, barcode, and histograms.

**A: Topology map.** The topology map is a key data abstraction within our design study. It is a 2D representation of the data that highlights its topological structure. We generate and validate such an abstraction through an active and cyclic design process with the scientists to arrive at its current form. The topology map encodes the locations of local extrema defined by their persistence and function values, as well as their connectivities (i.e., curves describing flow from a minimum to a maximum). Such a visualization is, in spirit, similar to the topological skeleton proposed in [25] and applied to nuclear probabilistic risk assessment [35, 36]. However, based on the new requirements outlined in Section 4, we have completely redesigned such a visual encoding to provide a topological summary that omits geometric information but preserves the underlying structure essential to understanding the data partitioning, thereby greatly improving its usability and scalability.

As illustrated in Fig. 3A, each local extremum is mapped onto a 2D plane, whose  $x$ -axis represents its *persistence* and the  $y$ -axis corresponds to its *function value* (i.e.,  $f(x,y)$ ). Therefore, local maxima (minima) move toward the top (bottom) of the display, respectively; more robust features appear to the right, whereas noisy ones tend to the left. Encoding function value to the  $y$ -axis is well aligned with the scientists’ understanding of typical 2D function plots where the dependent variables are mapped to the  $y$ -axis; in fact, the inverse coordinate plots used in HDViz (Fig. 2d) are often misinterpreted for violating this common notion. In addition, the local maxima (minima) are upward (downward) pointing red (blue) triangles for fast differentiation and counting.

Selecting the appropriate scale (i.e., persistence level) for data partitioning is essential during the exploratory process as it helps the user to understand the data hierarchy and sensitivity information. The above design also provides a natural separation between features and noise. The user is able to choose a scale by clicking anywhere in the plot, which creates a vertical line passing through the cursor location, separating the local extrema into those that represent robust topological features (grey region on the right) and those that represent topological noise (white region on the left). Extrema in the grey region are visualized together with their connectivities. Their sizes correspond to the point densities in their surrounding regions. Extrema in the white region are rendered with a default minimum size and therefore do not draw the user’s attention away from more salient features but still provide context.

Selection of the scale parameter is an interactive process that is hard to automate, where the user is free to explore and construct ROMs at arbitrary levels. In *persistence simplification* [14, 21], features and noise are assumed to exist on two separable scales, providing a heuristic to choose a scale (vertical line) that is a clear divider between well-separated clusters of extrema. Additional visual cues also help guide such a selection process. For example, in the fitness view, higher  $R^2$  scores typically correspond to better local fits of the model at a chosen scale. On the other hand, density information encoded by the sizes of the extrema influences the interpretation of the  $R^2$  score for a given partition, where a high  $R^2$  score for a partition with low point density may not be trustworthy.

Closed user feedback loops help us refine our visual encoding of the topological map. For example, the extrema in the grey region are connected via color-coded, user-adjustable, cubic Bezier curves, each of which represents a Morse-Smale cell (i.e. a data partition). Such a representation affords a level of flexibility to counteract visual clutter. Each partition is identified by one of nine colorblind-safe colors [50] that is used throughout the visual interface. The topological map is used as a high-level atlas to orient users in the data exploration process. It enables efficient comparisons among

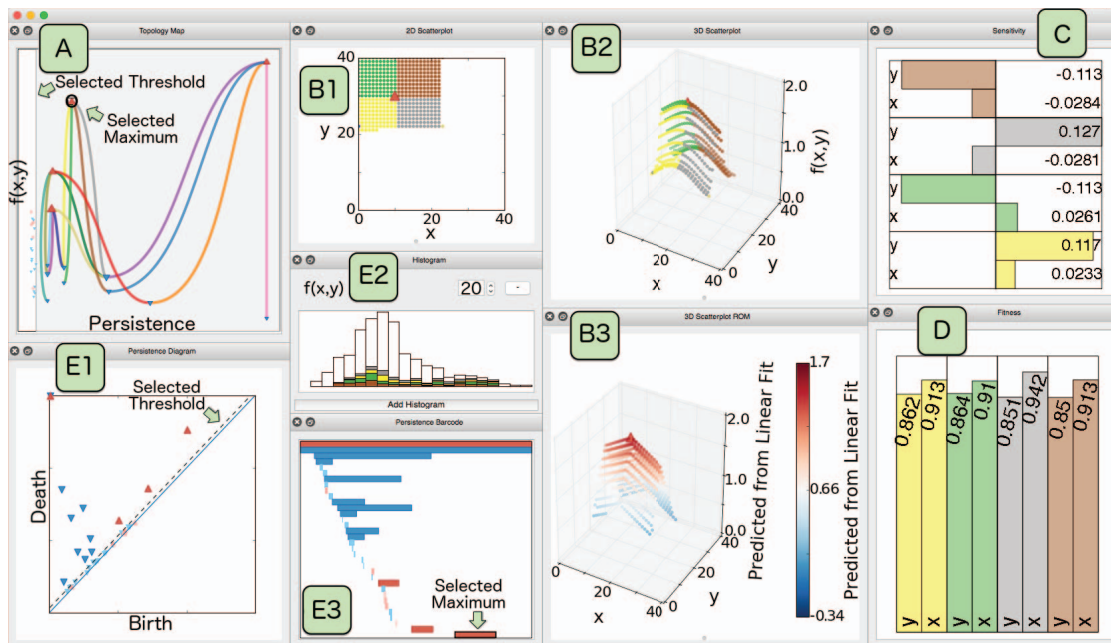


Figure 3: Our linked view visualization system using the same 2D test function of Fig. 1. The system includes (A) topology map, (B1-B3) scatterplots, (C) sensitivity view, (D) fitness view, (E1) persistence diagram, (E2) histogram, and (E3) persistence barcode.

partitions across multiple scales. The user can select local extrema and partitions via its interactive interface for in-depth analysis via the remaining views. We also defer additional geometric information to other views to avoid sensory overload.

In terms of scalability, in practice, with limited number of data points available and the appropriate choice of scales (potentially high-dimensional), nuclear datasets are typically analyzed with less than 10 partitions (e.g., [34, 35, 36]). For datasets with topological complexity that is beyond moderate, we would employ advanced graph drawing techniques such as edge bundling (e.g., [17]).

**B: Scatterplot projection.** The scatterplot projection is a common tool familiar to nuclear scientists. It allows the user to select up to three dimensions to be mapped to spatial coordinates, and a potential fourth dimension to be mapped to color. The dimensions of choice include the input parameters, the observed and predicted output parameters, and the residuals of the ROM. The users are therefore provided with detailed spatial information on demand. The 2D height function example in Fig. 3 includes a 2D scatterplot (involving two inputs  $x$  and  $y$  in B1), a 3D scatterplot (involving  $x$ ,  $y$ , and an observed output  $f(x,y)$  in B2), and a 3D scatterplot for the local ROMs (involving  $x$ ,  $y$ , and the predicted output).

**C: Sensitivity view.** We show per dimension coefficients associated with each partition of the data in signed, horizontal bar chart format. The coefficients used include the linear coefficients, the PEAR, and the SPEAR. The user therefore gains first derivative behavior for each selected partition. There are two important pieces of sensitivity information to convey in our visual encoding: the sign and the relative magnitude of the different coefficients. Using signed bar charts, this information becomes available at a glance, and the ubiquity of bar charts ensures their universal interpretation. These bar charts are clustered by partition for easy comparison.

**D: Fitness view.** For each partition, the fitness view reports the fit accuracy as well as its incremental improvement by increasing the dimensionality of the fit. Based on the linear coefficients described in the sensitivity view, the dimensions are ordered by their magnitude and visualized via vertical bar charts. Based on this sorted order of dimensions as a heuristic, we build lower-dimensional linear fits beginning with only the dimension with the largest coefficient in magnitude. We then iteratively add one dimension at a time and recompute an updated linear model. For an  $m$ -dimensional dataset,

we will end up with  $m$  different linear fits and for each fit, we compute the  $R^2$  score given in Section 3. The use of vertical bar charts conveys the stepwise improvement of adding a dimension to the regression model. Typically (but not always), the largest changes in  $R^2$  score occur at the beginning, and we are interested to know at what point the value added by increasing the dimensionality becomes negligible, signifying potentially extraneous dimensions.

**E: Secondary visual encodings.** We include a few secondary visual encodings to enhance and validate insights obtained from the primary ones. The persistence diagram is the classic tool in the form of a 2D scatterplot used for separating signal from noise [19]. In a nutshell, a point in the persistence diagram corresponds to a topological feature represented by the pairing of two critical points. The *persistence* of a point (and its corresponding feature) in the diagram is its distance to the diagonal. When selecting an appropriate scale for partition-based SA, the chosen vertical line in the topology map corresponds to a dotted line in the persistence diagram; a large separation between clusters of extrema in the topology map corresponds to a large separation between clusters of points in the persistence diagram.

The persistence diagram provides a standard and less cluttered view of the distribution of topological features in the data, and offers a complementary and validating alternative when selecting the appropriate scale. In addition, we also include a persistence barcode (see [8] for details) that encodes similar information as the persistence diagram as another alternative for visual comparison. Histograms are provided on demand and allow the user to visualize the distribution of inputs, outputs, and various computed values on a per partition basis. Histograms also provides an interactive filtering system. These alternative visual encodings are included as part of our parallel prototyping stage, and they are implemented in our final tool to offer diversity and increase efficacy.

## 6 IMPLEMENTATION

During the *implement* stage of our design study, we carefully choose algorithms, techniques, and programming languages to meet the design requirements of the nuclear scientists, addressing issues such as scalability and usability. Our implementation is integrated into RAVEN, an uncertainty quantification and probabilistic risk assessment tool actively being developed by and for nuclear scientists.

This creates a platform with good exposure for the new workflow being adopted by the scientists. Close user interactions help us refine our design and implementation in an iterative process. RAVEN is written in Python with a collection of C++ bindings for back-end algorithms. The approximate MSC computation and our costumed version of MSR are implemented in C++, and the graphical interface is implemented using the PySide binding of Qt. Such a programming environment supports rapid software prototyping and ensures tight integration with the existing RAVEN Python code. In addition, our modular implementation and linked view design [44] are also suitable for extending and expanding the visualization capabilities of RAVEN in the future.

## 7 DEPLOYMENT & EVALUATION: NUCLEAR FUEL DESIGN

The final *deploy* stage of our design study involves software release and evaluation. To evaluate the efficacy of our design and to gather feedback from the users, our framework is applied to an actual simulation being studied by the scientists involving nuclear fuel performance. As described in Section 4, the deployment is tightly integrated into the design stage as a feedback loop, allowing both the user and the designer to exchange ideas on the data and the design. We recount such an iterative process below.

### 7.1 Data From Nuclear Fuel Analysis

We consider an analysis of a nuclear fuel rodlet simulation performed using the BISON software [28], a modern finite-element based nuclear fuel performance code. The rodlet is axisymmetric and composed of 10 stacked  $\text{UO}_2$  pellets surrounded by a zirconium alloy shield known as the cladding. We track the midplane von Mises stress occurring on the 3D cladding. High stress can cause the cladding to crack and allow radioactive gas to leak into the plant environment. The simulation looks at a ramping of the linear power in the reactor from time  $t = 0$ , up to  $t = 10000$  (seconds), whereupon the power level maintains a constant value for the remainder of the simulation. The linear power begins at 0 W/m at  $t = 0$  and linearly climbs to a value of 25000 W/m before leveling off.

The goal is a better understanding of the physics happening at the *contact point* that occurs when the fuel rodlet expands to the point of touching the cladding. The stress on the cladding at  $t = 0$  is due to a compressive force from the water pressure outside the cladding. As fission occurs, the fuel rod expands as it is heated due to thermal expansion and swelling from the release of fission gas within the microstructure of the fuel. Once contact is made, thermal expansion (of the cladding) exerts a force that counteracts the compressive force from the water pressure, and therefore the stress in the cladding decreases until these forces reach an equilibrium. After the equilibrium point, the expansive forces on the cladding become dominant, causing stress on the cladding as it expands.

In the above scenario, contact is not indicative of a failure state, and is actually expected in these types of environments. The described problems arise only when the stress in the cladding becomes too high. For this study, the scientists vary three input parameters during the simulation: (a) the linear power scaling factor (**power\_scalef**), a multiplier for the previously described ramping linear power; (b) the grain radius scaling factor (**grainradius\_scalef**), a multiplier for the size of microstructure elements known as the grains and related to the swelling caused by the fission gas; and (c) the thermal expansion coefficient for the fuel rodlet (**thermal\_expansion**), which dictates how quickly the rod expands and thus how quickly it contacts the cladding. The output parameter of interest is the final midplane von Mises stress **midplane\_stress** (a scalar quantity derived from the Cauchy stress tensor useful in determining at what point the cladding may yield/crack) recorded after a simulation time of  $t = 10^6$  seconds. All parameters are scaled using z-score standardization to align with both domain and algorithmic practices.

### 7.2 Anomaly Detection in an Initial Dataset

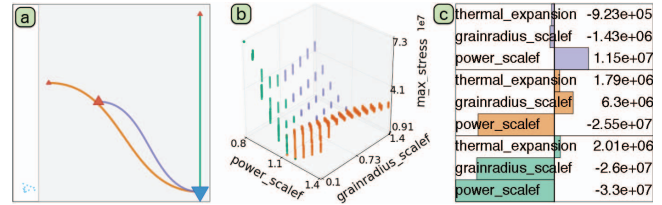


Figure 4: SA for the initial nuclear fuel dataset. (a) Topological map used to separate signal from noise. (b) Scatterplot projecting the most significant input **power\_scalef**, **grainradius\_scalef**, and the output **midplane\_stress**. (c) Linear coefficients.

Exploration begins with an initial dataset sampled from a uniform  $10 \times 10 \times 10$  grid of the parameter space. During the exploration process illustrated in Fig. 4, the scientists notice an unexpected behavior within the sensitivity view. An increase in the **thermal\_expansion** of the fuel is expected to it to expand more rapidly and come into contact with the cladding sooner. The result would cause everything to precipitate faster: a simulation reaching the equilibrium point leads to a higher stress in the cladding; a simulation ending before reaching the equilibrium point (exhibited via lower values of **power\_scalef**) results in a lower stress. The expectation is that the higher the **thermal\_expansion** is, the higher the stress becomes. However, the linear coefficients for **thermal\_expansion** across partitions in the sensitivity view contradict such an expectation: (a) **thermal\_expansion** is positive for the green and orange partitions when **power\_scalef** is low, and increases when approaching the equilibrium (located at the intersection of the three partitions); (b) **thermal\_expansion** is negative for the violet partition when **power\_scalef** is high, and decreases past the equilibrium. PEAR and SPEAR coefficients (not shown here) exhibit similar behaviors.

After further investigation with the fuel experts, simulation parameters aside from the three sampled were found to be improperly initialized, leading to this anomaly in the initial dataset. This is a very important observation as this particular dataset is being used by multiple ongoing projects where the validity of this dataset is crucial to their success. Such an anomaly in the dataset itself would not have been exposed via a global SA since the problem was detected by comparing the behavior of an input parameter from one partition to another where the partitions carry actual physical meaning.

### 7.3 Workflow With a New Dataset

After fixing the bug associated with the simulation input, a new dataset is generated for SA from 9517 simulations using Monte Carlo sampling of the three input dimensions from independent distributions. Starting with the topology map in Fig. 5a, a large horizontal gap between two clusters of extrema signifies well separation between signal and noise in the data. The scientists therefore select a scale (a vertical line) that preserves the three extrema in the grey region as topological features, resulting in two partitions of the data domain. Such a selection is also supported by observing a large gap between two clusters of points within the persistence diagram (Fig. 5b), where one cluster contains points near the diagonal  $y = x$  and the other contains points far away from the diagonal. As a first order approximation, the scientists build local linear regression models for these two partitions.

The resulting linear coefficients are shown in Fig. 5d where the **power\_scalef** dominates the behavior of the **midplane\_stress**. Furthermore, the fitness view (Fig. 5e) demonstrates that little to no information is gained by incorporating the remaining two dimensions, in either partition of the data. The fitness view also shows that the blue partition is not well described by a linear fit of any number of dimensions (i.e., with all three  $R^2$  scores valued roughly at 0.79). The scientists investigate further by projecting the data onto a

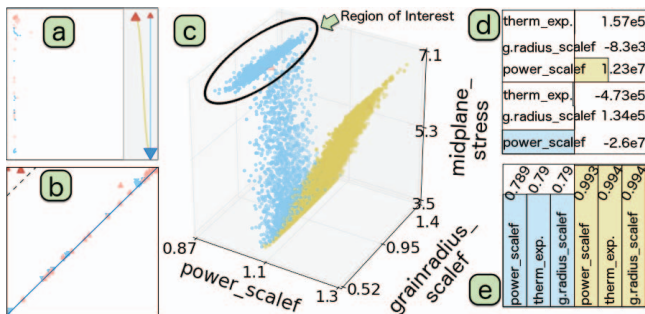


Figure 5: SA of the new nuclear fuel dataset: (a) topology map, (b) persistence diagram, (c) linked scatter plot projection, (d) linear coefficients, and (e) fitness view with stepwise  $R^2$  scores.

scatterplot (Fig. 5c) that includes the most sensitive input dimension (**power\_scaler**) and the output dimension (**midplane\_stress**). From this scatterplot, they detect the nonmonotonic behavior of a region of interest (ROI) within the blue partition, which has low **power\_scaler** and high **midplane\_stress**. The scientists then focus on a more refined analysis at a finer scale to try to capture the behavior of the ROI within its own partition.

Fig. 6 shows the results after decomposing the domain into three and four partitions at finer scales. The scientists, guided by both the topology map and the scatterplot view, iteratively choose finer and finer scales until the ROI separates itself from the larger blue partition. The first level of refinement produces three partitions in the data (Fig. 6a). Compared to the approximation with two partitions (Fig. 5c), the newly constructed magenta partition has relatively low point density (as shown in Fig. 6b) and does not correspond to the ROI. Under the second level of refinement (Fig. 6c), the ROI forms its own partition in green, as illustrated in Fig. 6d. In addition, there is significant improvement in the fitness for the blue region. That is, the three  $R^2$  scores increase from roughly 0.790 to 0.898 (Fig. 7). Therefore, extracting the desired ROI requires two additional levels of refinements.

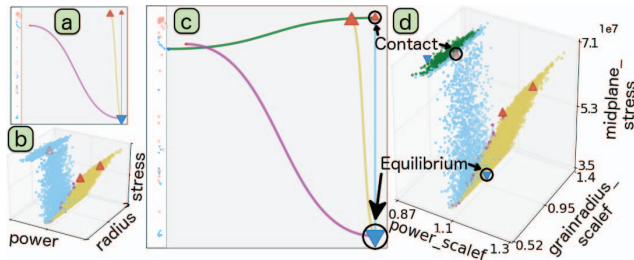


Figure 6: SA of the new nuclear fuel dataset under two refined settings: topology maps and scatterplots with three partitions (a)-(b) and four partitions (c)-(d), respectively.

Under the refined setting with four partitions, the scientists are able to obtain insights that are aligned with their expectation and domain knowledge. Using topology-based domain partitioning allows them to decompose the domain in a physically meaningful way. In particular, the four partitions within the data domain are shown to correspond to various stages of the simulation. The scientists focus on examining the characteristics of each partition and how the partitions interface with one another. First, the interface between the green and blue partitions represents the *contact* point where the fuel touches the cladding (Fig. 6d). Within the green partition (which has very low **power\_scaler** values), the net pressure acting on the cladding originates from the external water pressure. Second, the interface between the blue and the combined magenta and gold partitions corresponds to the *equilibrium* point. The blue partition represents the simulations where the expansive forces of the cladding begin to counteract the compressive water pressure force. Within the blue partition, as **midplane\_stress** decreases and

Fitness view		Linear Coefficients		Global Sensitivity Analysis	
power_scaler	0.894	thermal_expansion	3.8e+05	Linear Coefficients	
thermal_expansion	0.898	grainradius_scaler	6.95e+05	thermal_expansion	-4.47e+04
grainradius_scaler	0.898	power_scaler	1.27e+07	grainradius_scaler	7.18e+04
power_scaler	0.789	thermal_expansion	1.58e+05	power_scaler	-7.73e+05
therm_exp.	0.79	grainradius_scaler	-7.54e+03	CCA Structural Coefficients	
power_scaler	0.993	power_scaler	1.23e+07	thermal_expansion	-0.0404
therm_exp.	0.993	thermal_expansion	-7.65e+04	grainradius_scaler	0.0792
grainradius_scaler	0.994	grainradius_scaler	1.99e+04	power_scaler	-0.996
power_scaler	0.789	power_scaler	2.97e+06	midplane_stress	1
therm_exp.	0.79	thermal_expansion	-8.2e+05	PEAR	
grainradius_scaler	0.994	grainradius_scaler	1.98e+05	thermal_expansion	-0.00279
power_scaler	0.994	power_scaler	-3.77e+07	grainradius_scaler	0.00547
therm_exp.	0.789	thermal_expansion	-0.353	power_scaler	-0.0688
grainradius_scaler	0.998	grainradius_scaler	0.0208	SPEAR	
power_scaler	0.998	power_scaler	0.999	thermal_expansion	-0.0115
thermal_expansion	-0.00187	thermal_expansion	-0.00933	grainradius_scaler	0.00276
grainradius_scaler	0.00995	grainradius_scaler	0.00405	power_scaler	0.116
power_scaler	0.997	power_scaler	0.999		
thermal_expansion	-0.0536	thermal_expansion	-0.086		
grainradius_scaler	-0.0363	grainradius_scaler	-0.0364		
power_scaler	0.994	power_scaler	0.992		
thermal_expansion	-0.00471	thermal_expansion	-0.0265		
grainradius_scaler	0.0251	grainradius_scaler	0.0192		
power_scaler	-0.945	power_scaler	-0.986		

Figure 7: Left: sensitivity information of the new nuclear fuel dataset under the refined setting with four partitions. Right: global SA of the same dataset.

**power\_scaler** increases, the simulation moves closer to the equilibrium. Finally, the remaining two partitions (gold and magenta) contain scenarios after the equilibrium point between compressive and expansive stresses, and therefore within these partitions, an increase in **power\_scaler** leads to an increase in the dominating expansive stress (i.e., **midplane\_stress**). In terms of sensitivity information (Fig. 7 left), **power\_scaler** has a strong positive effect on **midplane\_stress** across the partitions with the exception of the blue region, where it is strongly negative.

Finally, the scientists compare the results from the partition-based local SA (Fig. 7 left) with that of a global SA (Fig. 7 right). For the global SA, the linear coefficients and CCA structural coefficients [16] are used to identify **power\_scaler** as the most sensitive parameter, yet its sign heavily depends on the amount of data on either side of the contact and equilibrium points. Similarly, the nonmonotonic global behavior masks the sensitivity associated with **power\_scaler** for both PEAR and SPEAR coefficients. On the other hand, the topology-inspired, partition-based SA is able to capture three distinct behaviors in the data, and it highlights the high sensitivity associated with **power\_scaler** within each partition.

Using our framework, the scientists have validated the behaviors of a nuclear fuel simulation to be well aligned with their expectations. They are actively investigating higher-dimensional problems where topological partitioning could offer them additional insights that are not readily available via traditional visualization such as scatterplot projections. Our objective in validation has been confirmed by the scientists where they could perform SA faster and with higher accuracy. Our framework also offers a new paradigm in rethinking about SA via topology in nuclear engineering.

## 8 CONCLUSION

According to our collaborating scientists, our software is the *first* screening tool to enable understanding the dominant impacts of the uncertain parameters with respect to design figures of merit (e.g., internal pressure, stress, etc.). They also found it useful for ranking the uncertain parameters and for the construction of effective and powerful ROMs for an extensive UQ study. Finally, we demonstrated how our tool was able to quickly and effectively highlight anomalous results at the earliest stages of the fuel design process.

The following summary was provided by one of our collaborating scientists: Recent studies [6, 32, 40] have demonstrated the application of SA to the modeling of nuclear fuel behavior, where the considered scenarios have covered both steady-state and transient irradiation and different burnup levels. However, existing results have been presented in terms of output range given the whole input domain (i.e., global SA). Instead, the presented technique allows fuel designers to decompose the analysis into partitions based on

actual regimes of fuel behavior (e.g., open fuel-cladding gap or fuel-cladding contact). Fuel performance during these different regimes can be driven by different aspects (e.g., rod fill gas pressure or fuel-cladding contact pressure), and hence, such physically based decomposition may offer more meaningful insight into the specific situations targeted by the analysis.

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