



Limitations of the Exploratory Capacity of Genetic Algorithms for the Calibration of the HBV Hydrological Model

ESS 511 Master's Thesis

Author: Lionel Andrey, 08-294-969

Supervised by: Franziska Clerc-Schwarzenbach, Marc J. P. Vis

Faculty representative: Prof. Dr. Jan Seibert

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**Universität
Zürich** ^{UZH}

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Prof. Dr. Jan Seibert

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Department of Geography, University of Zurich

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Abstract

Hydrological models such as HBV (*Hydrologiska Byråns Vattenavdelning*) require the calibration of multiple interacting parameters. This process represents a high-dimensional and complex optimization problem where multiple distinct parameter sets yield similarly good performance (i.e., equifinality). Genetic algorithms (GAs) have been widely used for this calibration task. In this context, GAs search a parameter space containing many comparable optima, sometimes situated far away from each other. GAs must therefore balance broad exploration of different parameter space regions and efficient convergence toward high-performing local solutions. In the case of HBV, practical consequences of incomplete exploration include a systematic underestimation of model uncertainty, biased hydrological predictions if only a subset of possible parameter sets is identified, and reduced robustness of ensemble forecasts. While the exploratory capacity of GAs has been studied in general optimization contexts, it has not been explicitly assessed for the HBV parameter space. This thesis addresses this gap by analyzing how effectively GAs explore the HBV parameter space and by evaluating potential improvements to overcome identified limitations.

In the first part, the exploratory capacity of the basic GA used in HBV-light is analyzed using a reduced four-dimensional representation of the parameter space. This reduction is based on a Sobol sensitivity analysis, allowing the most influential parameters to be retained while maintaining computational feasibility. The resulting response surfaces are mapped at high resolution and characterized using topological data analysis. This allows the identification of high-performance regions within the parameter space, along with their structural properties. By running repeated GA calibrations on these mapped response surfaces, the thesis demonstrates that the GA generally converges rapidly toward large, high-performance regions but often fails to detect smaller optima. This limitation is linked to a rapid loss of GA population diversity. It is further reinforced by probabilistic biases favoring broader regions of acceptable performance over sharper (low volume), higher-performance local optima.

In the second part, a modified GA is developed to enhance the exploratory capacity by introducing diversity-based restart mechanisms, removal of previously explored regions,

and controlled elitism. The modified algorithm is tested in both reduced (4D) and full (13D) parameter spaces and compared with the basic GA. The results show that the modified GA can improve exploration in specific cases, particularly in reduced dimensionality. However, its performance in higher dimensions remains limited. In contrast, a new discrete version of the basic GA shows consistently strong optimization results, mainly due to improved sampling of sensitive regions at the edges of the parameter space.

Overall, the findings show that the performance of GAs is strongly influenced by the structure of the parameter space. Certain parameters in HBV, especially K2, play a key role in shaping this structure. The thesis demonstrates that current GA approaches can fail to detect relevant solutions. Consequently, calibration results partly reflect algorithmic limitations rather than the full range of plausible hydrological behaviors, affecting runoff simulations and uncertainty estimates. The thesis concludes that while algorithmic modifications can partly address these issues, alternative strategies such as parameter range refinement or segmented calibration may be more effective to improve model robustness. These results contribute to a better understanding of the interaction between optimization algorithms and hydrological models and support more robust calibration practices.

Introduction

Hydrological models are widely used for catchment process understanding (Rosbjerg and Madsen, 2005), flood or drought predictions (e.g., Brunner et al., 2019; Liechti et al., 2013; Liechti and Zappa, 2016), and runoff predictions under climate or land-use change (e.g., Hakala et al., 2019; Seibert and Van Meerveld, 2016). Thus, they represent a very useful tool to support political decisions. Throughout the years, many different hydrological models have been developed, with focus on different processes and data availability (e.g., *Génie Rural à 4 paramètres Journalier (GR4J)* (Perrin et al., 2003), PREVAH (Viviroli et al., 2009) or TOPKAPI (Ciarapica and Todini, 2002)). Indeed, each model has its own specificity and must be applied with care depending on the research questions (Beven, 2001). A typical and widely used bucket-type (rainfall-runoff) hydrological model is the HBV (*Hydrologiska Byråns Vattenavdelning*) model (Bergström, 1976), that has been developed by Sten Bergström and colleagues at the Swedish Meteorological and Hydrological Institute SMHI since the 1970s. What makes HBV attractive and powerful is its simplicity: HBV displays remarkably accurate results when considering the very low amount of input data needed (Seibert and Bergström, 2022): precipitation, temperature, potential evapotranspiration and runoff (for calibration) timeseries. More recent semi-distributed models such as PREVAH (Viviroli et al., 2009) and fully-distributed, physically based models such as TOPKAPI (Ciarapica and Todini, 2002) have demonstrated strong performance in runoff prediction, but the amount of input data needed (i.e., wind speed, relative humidity, soil moisture, cloud cover transmissivity, etc.) makes them more challenging to use. Indeed, many catchments in the world are not equipped with instruments capable of such measurements. Even when all necessary input data are accessible, the use of such models is complex and needs greater computer capacities compared to simple models like HBV. Because of this parsimonious approach, HBV is widely used worldwide for research and runoff predictions (Seibert and Bergström, 2022). With the goal of simplifying further the use of HBV, Seibert and Vis (2012) have later developed HBV-light. This version presents an optimized and user-friendly interface while keeping the model the same.

As for most bucket-types hydrological models, the calibration of catchment-specific parameter values is required. For this calibration process, the comparison of observed and simulated runoff is quantified with a goodness-of-fit measure, also called objective function (Beven, 2012; Pool et al., 2018). The idea is to find parameter sets that optimize the value of the objective function, represented as a response surface over the parameter space (schematic representation in Figure 1).

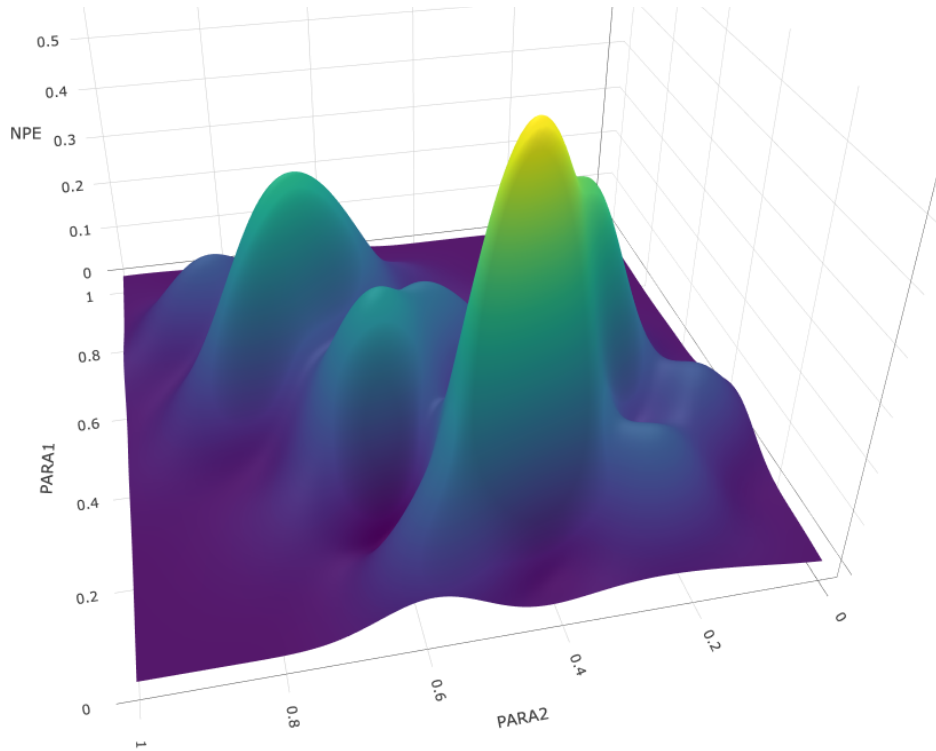


Figure 1: Schematic representation of a 2D parameter space, with the non-parametric efficiency NPE (Pool et al., 2018) as an exemplary objective function. The response surface is complex, with multiple local optima (green) and a global optimum (yellow).

Because of the number of parameters to estimate, the calibration process represents a high-dimensional optimization problem where the *landscape structure* of the response surface is vast and complex. In the case of HBV, the number of parameters to estimate can vary depending on the model settings (usually about 13). An exhaustive search (Monte Carlo method or brute force) is computationally impossible: testing only 10 values for each parameter would require 10^{13} model runs. This would take years to compute, even on the most powerful supercomputers, only for the calibration of one catchment, whereas in many recent papers hundreds or thousands of catchments are analyzed (e.g., Beck et al., 2016; Clerc-Schwarzenbach et al., 2024; Meyer Oliveira et al., 2023). A traditional gradient-based optimization method is not suitable because the response surface

is highly non-linear and multimodal (Kavetski et al., 2006) (see Figure 1). This is mainly due to the equifinality principle: multiple distinct parameter sets yield similarly good performance through compensation mechanisms (Beven and Freer, 2001).

For these reasons, optimization algorithms such as Genetic Algorithms (GAs) (Holland, 1984, 1962), Differential Evolution (Storn, 1997), and Particle Swarm Optimization (Kennedy and Eberhart, 1995), have been developed to efficiently explore complex surfaces. Among these, GAs are particularly attractive due to their population-based search strategy, which aims to combine exploration (i.e., the capacity to scan and reach different high-performance regions) and efficiency (i.e., the capacity to refine solutions within the different high-performance regions explored and find their respective local optimum). Therefore, Seibert (2000) implemented a GA as the default calibration tool in HBV-light. GAs mimic the genetic evolution by recombining population members (i.e., parameter sets) based on their fitness (i.e., objective function score), with fitter members having higher chances to be selected for recombination. The process is represented in Figure 2.

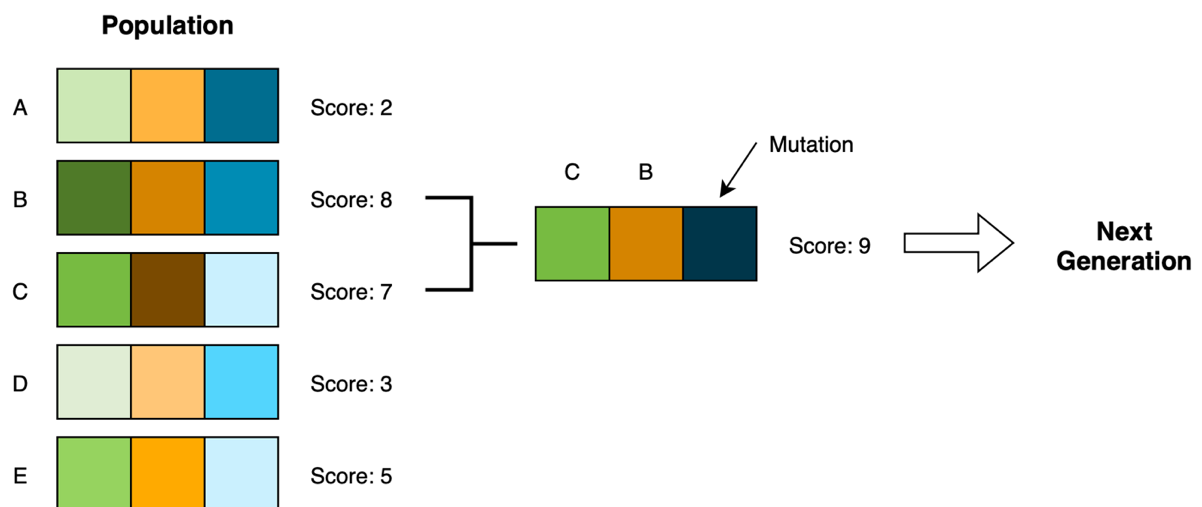


Figure 2: Genetic Algorithms mimic the genetic evolution through the following process: An initial random population (members A-E, representing parameter sets; with three different genes (green, brown and blue), representing single parameters) is tested for fitness (score, representing the objective function). Fitter members have higher chances of being selected for recombination (B, C) and passing their individual genes to a newly recombined member, with some chance of mutation. A new generation is created so with a similar number of members within the population. The process continues for a given number of generations or runs. The best member of the current generation is also kept in the new generation (elitism) to ensure to always conserve the best parameter set found so far. Such an approach balances efficiency (recombination of genes) with exploration (mutations).

While many studies showed the superiority of such optimization algorithms (Duan et al., 1992; Seibert, 2000) or compared the efficiency of different non-gradient-based algorithms (e.g., Napiorkowski et al., 2022), this past research focused solely on the value of the objective function, with attempts to optimize it. More precisely, no explicit assessment of the algorithm's exploratory capacity within the high-dimensional parameter space has been made for HBV so far. Such an exploration analysis would enable to test more precisely which high-performance zones are detected by the algorithm, and potentially which ones are not. If the GA converges prematurely into a narrow region of the parameter space, important and equally valid solutions could remain undiscovered. Practical consequences of incomplete exploration include a systematic underestimation of model uncertainty, biased hydrological predictions if only a subset of possible parameter sets is identified, and reduced robustness of ensemble forecasts (Liechti and Zappa, 2016). For this reason, it would be of great use for the optimization algorithm to be able to detect all (or at least several) of the reasonably well performing local optima in the parameter space when executing the algorithm multiple times.

This thesis focuses on this task, for the precise case of the GA used in the HBV-light hydrological model, with the following research questions for the first part of the thesis:

1. How well does the GA explore the parameter space of the HBV-light model and identify high-performing parameter sets? Is the GA capable of identifying *all* regions of high performance in the parameter space, and finding their respective local optimum; or does the GA converge prematurely into a limited subset of solutions? How consistent are these outputs across different GA calibrations?

The exploratory capacity of the GA is defined in this thesis as the capacity to discover all high-performance clusters within the parameter space, more than focusing on detecting the best cluster. The methodology consists first of analyzing the *landscape structure* of the response surface in a reduced 4D dimensionality (i.e., only four model parameters are varied). This is done by systematically sampling the reduced space and represents the compromise of using as many parameters as possible (i.e., four) while still being computationally reasonable. The behavior of the GA is then tested on this known response surface.

After answering the previous questions, the second part of the thesis answers the following questions:

2. How can the GA be modified to compensate for its weaknesses, especially the rapid loss of diversity within its population? More precisely, can a specific restart routine increase the exploratory capacity of a modified GA by maintaining population diversity?

Here, the methodology aims to adapt the existing GA and to analyze its behavior in the reduced dimensionality (4D) before testing it in the full dimensionality (13D). Systematic comparisons are made with the basic GA.

First Part: Exploratory Capacity of the Genetic Algorithm

Data and Methods

HBV-light Setup

Model and Definitions

To evaluate the exploratory capacity of the GA in the HBV-light model, it is first necessary to present the model. HBV is a typical bucket-type (rainfall-runoff) hydrological model composed of several interconnected routines representing dominant hydrological processes (Seibert and Vis, 2012). These include a snow routine controlling accumulation and melt; a soil routine computing evapotranspiration and recharge; and a response function consisting of linear reservoirs that simulate runoff generation and routing. Each routine is executed separately for different elevation zones and is controlled by a set of parameters that regulate water fluxes between storages. Because the model is run at catchment scale, parameter values represent an average for the whole catchment. Thus, they generally do not reflect true physically meaningful values (Bergström, 1991). The necessary input data consist of precipitation, temperature, potential evapotranspiration and runoff (for calibration) timeseries. The model is presented schematically in Figure 3 and model parameters are listed in Table 1.

Next, it is necessary to clearly define the environment in which the GA exploration takes place. In this thesis, this environment is referred to as the parameter space, which represents all possible combinations of model parameter values. The *landscape structure* (or simply *structure*) of the parameter space describes how model performance varies across these parameter combinations. In other words, it defines the shape of the response surface associated with the objective function, including the number, location, and extent of high-performance regions (i.e., local and global optima). This *structure* is crucial, because the GA can only identify solutions that exist within this *landscape*, and its exploratory capacity depends on how effectively it navigates this complex surface. Consequently, this *landscape structure* is determined by two main elements: the objective function used to evaluate performance, and the parameter ranges considered.

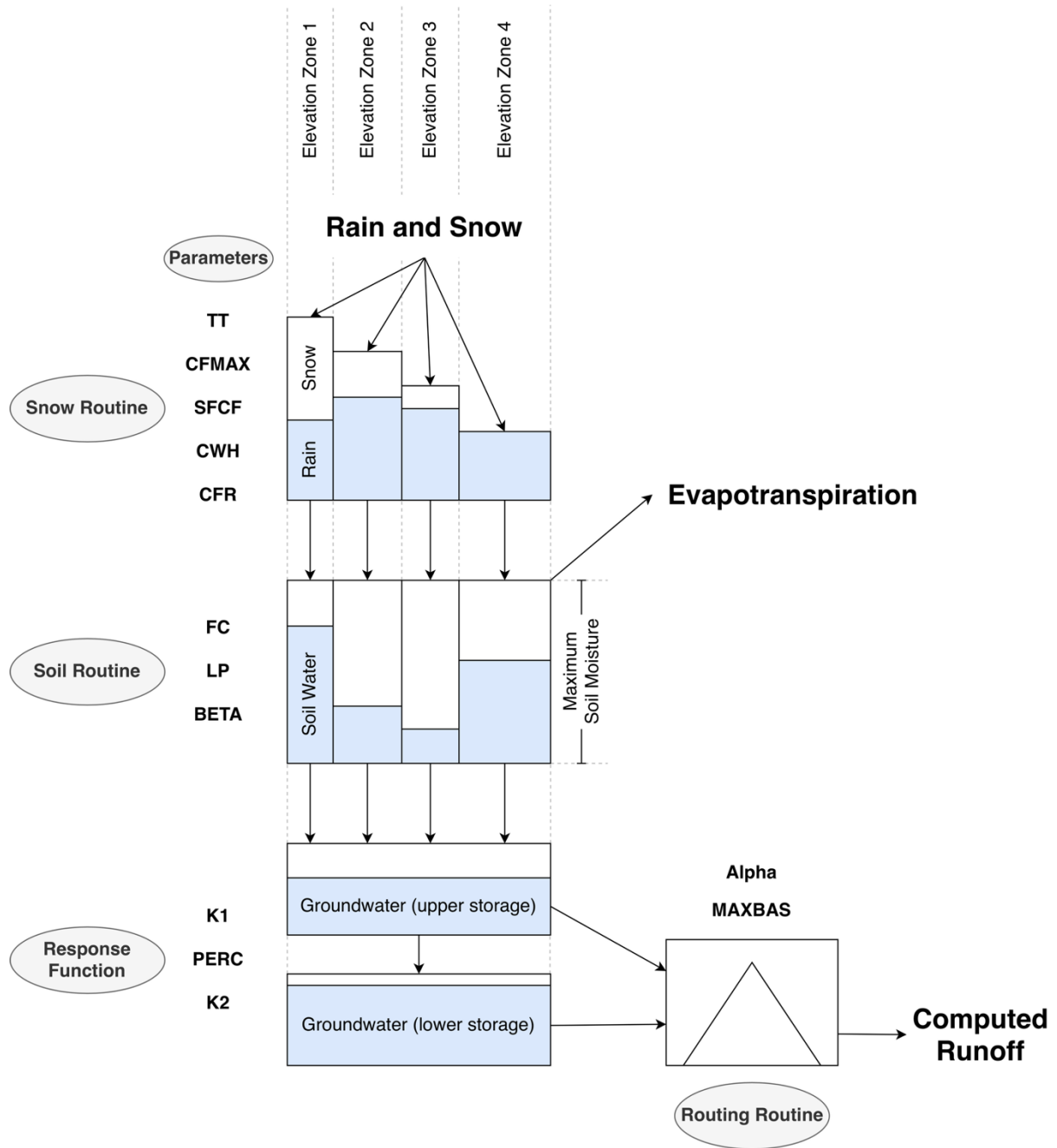


Figure 3: Schematic representation of the HBV model. A precise description of the parameters is presented in Table 1.

Objective Function

For this thesis, we chose the non-parametric efficiency (NPE) metric developed by Pool et al. (2018) as the objective function. The NPE is based on and adapted from the widely used Kling-Gupta efficiency (KGE) metric (Gupta et al., 2009). The assumptions made when using KGE (data normality, data linearity, and absence of outliers) are very often not justified for runoff data: high-flow events are rare, leading to a rather right-skewed distribution. The NPE removes these assumptions by using a ranking-based method. It

therefore concentrates on the dynamics of the hydrograph rather than on discharge volumes (Pool et al., 2018). Moreover, given its close relation to KGE, the response surface obtained with NPE can be expected to share a similar structural form, making the results of this thesis transferable to KGE-based studies.

HBV Parameters

We set the parameter ranges used in this thesis to the values used on the most recent studies by the Hydrology and Climate group (H2K) at the University of Zurich UZH (e.g., Clerc-Schwarzenbach et al., 2024; Clerc-Schwarzenbach and Do Nascimento, 2026). These values typically follow physically meaningful ranges where applicable (Seibert, 2000; Seibert and Vis, 2012) and have been modified slightly to better represent local realities. For European catchments (excluding Switzerland), two parameters (i.e., CFR and CWH) are not varied during typical analyzes, as done by Clerc-Schwarzenbach and Do Nascimento (2026). Also, the range of K2 is generally adjusted for Swiss catchments. Table 1 shows these ranges, alongside typical literature values. More precise information about the parameters is found in the cited literature, as this information is not central for this thesis. More precise information about the catchments analyzed and the difference between European and Swiss catchments is discussed later.

Table 1: Parameter ranges used in this thesis (highlighted in grey) compared with literature values.

Parameter	Description	Unit	Range used (Swiss catchments)	Range used (European catchments, excluding Switzerland)	Range (Seibert, 2000)	Range H2K group UZH ¹
Snow routine						
TT	Threshold temperature (precipitation as snow or rain)	°C	-2; 2.5	-2; 2.5	-1.5; 2.5	-2; 2.5
CFMAX	Degree-day factor	mm °C ⁻¹ d ⁻¹	0.5; 10	0.5; 10	1; 10	0.5; 10
SFCF	Snowfall correction factor	-	0.5; 1.2	0.5; 1.2	0.5; 1.2	0.5; 1.2
CWH	Water holding capacity of snow	-	0; 0.2	0.1; 0.1 (not varied)	0; 0.2	0.1; 0.1 (not varied)
CFR	Refreezing coefficient	-	0; 0.1	0.05; 0.05 (not varied)	0; 0.1	0.05; 0.05 (not varied)

¹E.g., Clerc-Schwarzenbach and Do Nascimento (2026)

Soil routine						
FC	Soil moisture maximum	mm	100; 1000	100; 1000	50; 500	100; 1000
LP	Threshold of reduction of evaporation	-	0.3; 1	0.3; 1	0.3; 1	0.3; 1
BETA	Shape coefficient	-	1; 5	1; 5	1; 6	1; 5
Response routine						
K1	Recession coefficient (upper storage)	d ⁻¹	0.01; 0.2	0.01; 0.2	0.05; 0.3	0.01; 0.2
K2	Recession coefficient (lower storage)	d ⁻¹	0.00005; 0.1	0.001; 0.1	0.001; 0.1	0.001; 0.1
Alpha	Non-linearity coefficient of runoff	mm °C ⁻¹ d ⁻¹	0; 1	0; 1	-	0; 1
PERC	Maximal flow from upper to lower storage	mm d ⁻¹	0; 4	0; 4	0; 4	0; 4
MAXBAS	Routing, length of weighing function	d	1; 5	1; 5	1; 7	1; 5

Genetic Algorithm Settings

The settings of the GA directly influence its search capacity. For this thesis, we chose to work with the default values of the GA in HBV-light (recombination and mutation rates of 0.9 and 0.1 respectively; one population of 50 members; no population exchange; no optimization between sets), as most studies used these values (e.g., [Clerc-Schwarzenbach et al., 2024](#); [Meyer Oliveira et al., 2023](#); [Van Tiel et al., 2020](#)). Furthermore, we did not use any Powell optimization.

Throughout the thesis, we distinguish between runs, generations, and milestones: A run refers to a single evaluation of the hydrological model (as used by the GA) to test a newly created parameter set. A generation corresponds to one iteration of the GA, consisting of a fixed number of runs equal to the population size (here 50 runs per generation). Finally, milestones denote specific numbers of runs at which the state of the GA is recorded and analyzed (e.g., milestone_50 corresponds to the state of the GA after 50 runs: first generation; and milestone_1000 corresponds to the state of the GA after 1,000 runs: 20th generation).

The calibration period consisted of the ten years from 1 January 2001 to 31 December 2010, preceded by a two-year warm-up period.

Catchments

Because of the computationally high number of analyses done for each catchment, only a small sample of catchments could be analyzed in this thesis. Generally, when performing a GA calibration on the full 13D response surface, it can be observed that catchments react differently. When repeating GA calibrations many times for the same catchment, the resulting objective function values associated with the parameter sets selected by the GA can be very variable. We assumed that catchments with a larger objective function value range are multimodal. This means that the response surface presents different local optima that are reached by the GA in different calibrations. This is the kind of *landscape structure* that is interesting to analyze regarding the research questions. Catchments presenting smaller ranges are expected to be more straight-forward to calibrate, with only one zone constantly reached by the GA. Nevertheless, this could imply that the high-performance zone is very large and not fully explored, or that the GA misses other local optima completely. For these reasons, we analyzed catchments with both large and small objective function value ranges. We only considered meaningful cases, i.e., positive objective function values. Based on this, we selected a total of 10 catchments that display the largest (respectively the smallest) range from different European large-sample datasets: two catchments from the Spanish dataset BULL ([Senent Aparicio et al., 2024](#)), three catchments from the French dataset CAMELS-FR ([Delaigue et al., 2025](#)), two catchments from the German dataset CAMELS-DE ([Loritz et al., 2024](#)), two catchments from the British dataset CAMELS-GB ([Coxon et al., 2020](#)) and one catchment from the Czech dataset CAMELS-CZ (not yet published; personal communication with M. Jenicek and O. Ledvinka). These catchments are referred to as “European catchments” in the thesis. We used the KGE as objective function for this range assessment (10 GA calibrations per catchment), as the process was done already in another study ([Clerc-Schwarzenbach and Do Nascimento, 2026](#)) and results were recycled here. This does not affect the general conclusions of the thesis, as the response surfaces obtained with KGE and NPE are structurally very similar, as stated previously. Also, KGE was only used for catchment selection and the whole analysis was then computed on the NPE surface. Furthermore, we

added four catchments from the Swiss dataset CAMELS-CH (Höge et al., 2023), including different parameter ranges as described in Table 1. These catchments are referred to as “Swiss catchments” in the thesis. They were selected without a rigorous process, but were chosen for a large KGE range nevertheless. Table 2 is a summary of the different catchments that were analyzed in this thesis.

Table 2: Catchments analyzed in this thesis, ranked by KGE range of the outputs of 10 GA calibrations.

Catchment	Country	River	Gauge	KGE range	KGE max
Larger KGE ranges					
2155	CH	Emme	Wiler	0.6008	0.6141
2403	CH	Inn	Cinuos-chel	0.5184	0.7647
2426	CH	Seez	Mels	0.1741	0.7999
CZ000098	CZ	Košátecký potok	Košátky	0.1483	0.6088
ES000356	ES	-	Calamocha	0.1247	0.4123
DEBB0136	DE	Verlorenwasser	Wenzlow	0.1197	0.5794
DEBB0132	DE	Plane	Trebitz	0.1191	0.5403
GB000296	GB	Law Brook	Albury	0.1143	0.3743
5014	CH / FR	Le Doubs	La Cluse-et-Mijoux	0.0914	0.8165
Smaller KGE ranges					
GB000494	GB	Grwyne	Millbrook	0.0017	0.9273
FR001413	FR	Le Beuvron	Andrezé	0.0014	0.9173
ES001323	ES	-	Moraleja	0.0014	0.6468
FR000672	FR	Le Trieux	Saint-Péver	0.0013	0.9316
FR000730	FR	Le Pont l'Abbé	Plonéour-Lanvern	0.0010	0.9318

Methodological Process

To analyze the exploratory capacity of the GA, we followed a multi-step approach. First, we quantified parameter importance using Sobol indices, allowing us to identify which parameters primarily shape the *landscape structure*. Second, we reduced the parameter space to four dimensions to make the analysis computationally possible while preserving

the main characteristics of this *landscape structure*. Third, we analyzed the geometry of high-performance regions using topological data analysis (TDA), providing insight into how solutions are distributed within the *landscape*. Finally, we ran the GA on this mapped *landscape* to evaluate how effectively it explores these regions. For clarity, the overall methodological process is presented in [Figure 4](#) and described in detail in the following sections.

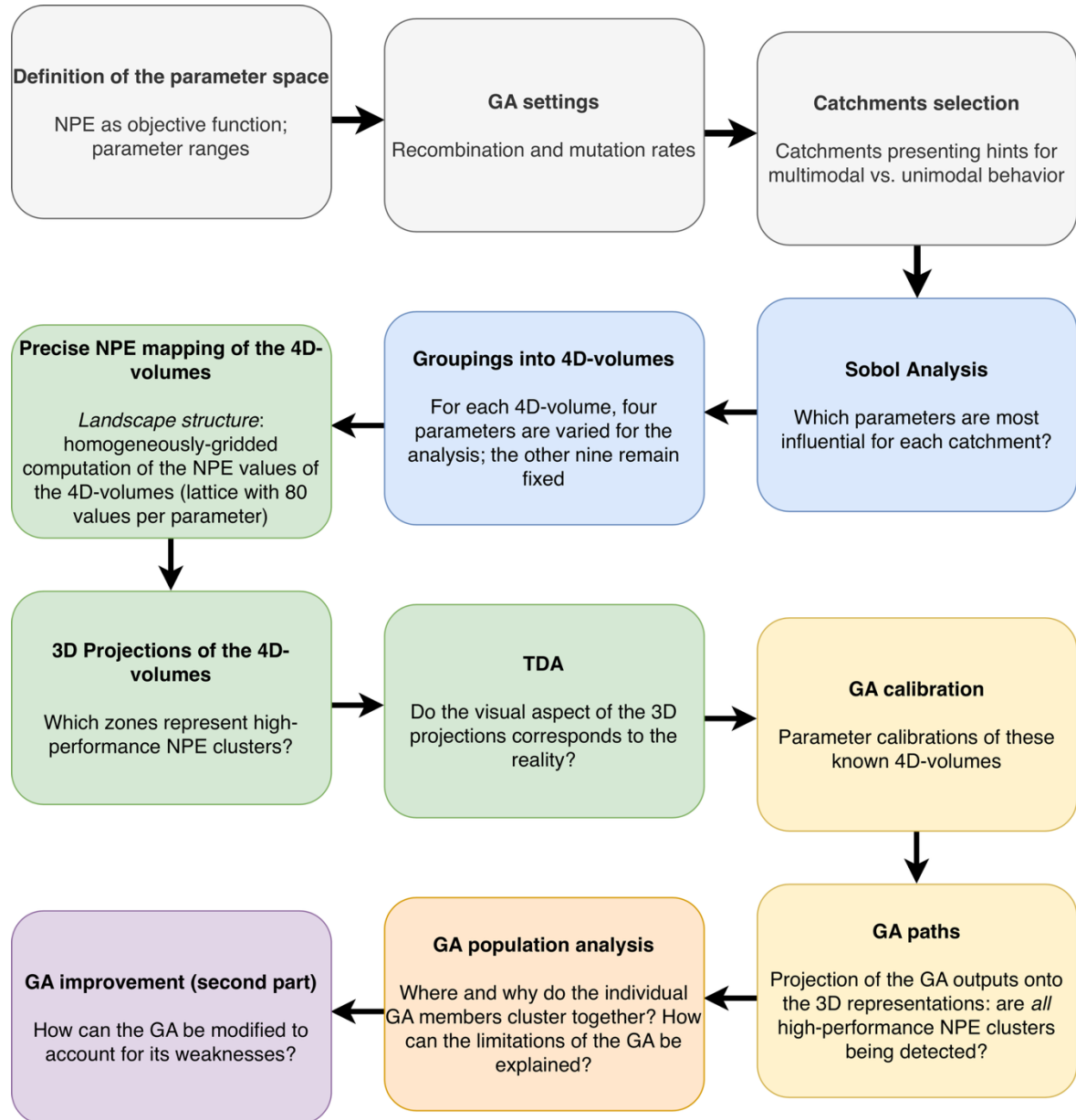


Figure 4: Schematic representation of the methodological process of the first part of the thesis. Grey boxes show the steps linked to the definitions and settings of the thesis; Blue boxes show the steps linked to the groupings into 4D-volumes; Green boxes show the steps linked to the NPE mapping of these 4D-volumes; Yellow boxes show steps linked to the GA calibration and representation; The orange box shows the deepened analysis of the GA mechanism; And the purple box shows the link into the second part of the thesis.

Dimension Reduction

To evaluate the exploratory capacity of the GA in HBV-light, the ideal case would be to have the full response surface mapped at high resolution. Such a surface, available for multiple catchments, would allow running the GA directly on it to assess which local optima are identified and which regions remain unexplored. For the same computational limitations as for the calibration process itself, this was unfortunately infeasible.

Instead, we adopted a reduced approach here, by lowering both dimensionality and resolution. Specifically, we mapped the response surface in four dimensions, with nine of the 13 parameters fixed at predefined values. We varied the remaining four parameters across their respective ranges at a resolution of 80 evenly spaced values, representing a homogeneously gridded 4D-volume with 40,960,000 values (regular lattice). This reduced approach balances resolution with computational feasibility, while still capturing the most important structural features of the response surface.

Sobol Analysis

We selected the four parameters spanning the 4D-volumes based on their sensitivity. We ranked parameter sensitivity through a Sobol sensitivity analysis (Sobol', 2001) conducted separately for each catchment. This variance-based method quantifies the contribution of each parameter to the overall variance in model output and therefore identifies the parameters with the greatest influence. We computed both first-order and total-order Sobol indices. The first-order index measures the effect of a single parameter on the model output while keeping all others constant. If the first-order effect of a parameter equals 1, all variability in output values can be explained by this single parameter. The total-order index, in contrast, measures the contribution of a parameter including both its direct effect and all its interactions with other parameters. The equations for the two indices are presented in Equation 1 and Equation 2, and an example is given in Figure 5. In these equations, Y denotes the model output whose variance is analyzed, and X_i represents an individual parameter whose contribution to this variance is quantified.

$$\text{first-order index: } S_i = \frac{\text{Var}_{X_i}(E[Y|X_i])}{\text{Var}(Y)} \quad (\text{Eq. 1})$$

$$\text{total-order index: } S_{T_i} = 1 - \frac{\text{Var}_{X_{\sim i}}(E[Y|X_{\sim i}])}{\text{Var}(Y)} \quad (\text{Eq. 2})$$

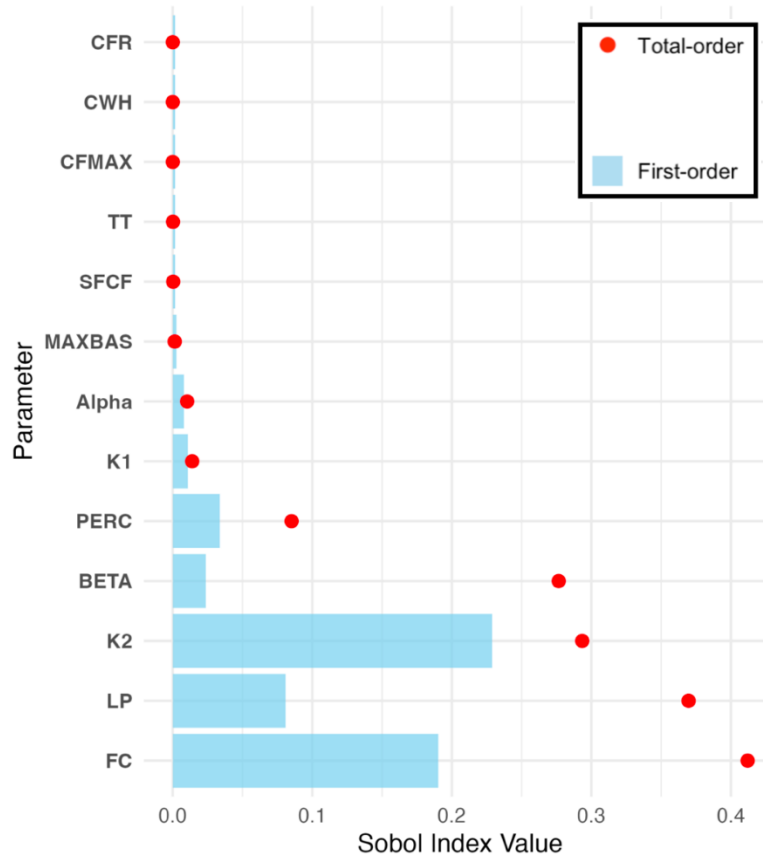


Figure 5: Example of a Sobol analysis: K2 presents the largest first-order effect, meaning that a considerable output variance is achieved by modifying this parameter only. On the other hand, FC explains the largest general output variance, due to the combination of its direct effect and the interactions with other parameters. For this parameter the difference between total-order and first-order ($0.41 - 0.19 = 0.22$) represents the output variance due to interactions only. CFR, CWH, CFMAX, TT, SFCF and MAXBAS do not have an impact on output variance at all, meaning that modifying the values of these parameters do not modify the output values. These parameters can be completely removed when calibrating HBV-light for this catchment. BETA, when modified alone, does not significantly impact the output values (low first-order index), but this parameter interacts greatly with other parameters (large difference between total-order and first-order). For this reason, and due to the principle of equifinality, the total-order is chosen for selecting the groupings into 4D-volumes.

Because testing every possible combination of parameter values to assess output variance was infeasible again, we used the Saltelli sampling design (Saltelli et al., 2010). This design provides an efficient way to select a subset of combinations of parameter values that can reliably capture the overall variation in the model output. The Saltelli design we used included $n = 1,400,000$ combinations of parameter values. We finally ranked the parameters according to the total-order indices, to more realistically account for the interaction effects among parameters, which is an important consideration regarding equifinality (Beven and Freer, 2001). Groups of four highly influential parameters are expected to provide a simplified but representative approximation of the 13D *landscape structure*.

Combinations of influential and less influential parameters, when compared with highly influential parameter groups, are expected to show how the reduced parameter space may evolve in higher dimensions. This, to a certain extent, allowed for an extrapolation attempt into the full 13D space.

4D-volumes Mapping

We studied how the GA behaves in two distinct situations: during early exploration of medium-performance regions, and near a local optimum (final adjustments). Beside the four varied parameters spanning the 4D-volumes, we fixed the remaining nine unvaried parameters to create these two distinct environments. Specifically, we used two types of fixed nine-parameters sets: a medium-performing set (exploration phase), and a high-performing set (near-optimum phase). To obtain these fixed parameter sets, we executed the GA twice for each catchment in the full 13D space. From one calibration, we selected a parameter set after 3,500 runs (70th generation). This represents the exploration phase. From another calibration, we selected a parameter set after 10,000 runs (200th generation). This represents the near-optimum phase. This setup allowed us to assess the exploratory capacity of the GA throughout the whole calibration process. [Table 3](#) summarizes the different 4D-volumes created, sampled and analyzed for each catchment.

Table 3: List of the 4D-volumes analyzed for each catchment. As an example, the 4D-volume 2155_4D_E represents a reduced 4D parameter space for the catchment 2155. The parameters ranked 5th to 8th in influence are varied, while the remaining nine parameters are fixed at values corresponding to a near-optimum configuration.

4D-volumes	Unvaried nine parameters fixed...	Sobol ranking of the four varied parameters
4D_A	During exploration (3,500 runs)	1, 2, 3, 4
4D_B	Near optimum (10,000 runs)	1, 2, 3, 4
4D_D	During exploration (3,500 runs)	5, 6, 7, 8
4D_E	Near optimum (10,000 runs)	5, 6, 7, 8
4D_J	During exploration (3,500 runs)	1, 4, 7, 10
4D_K	Near optimum (10,000 runs)	1, 4, 7, 10

Topological Data Analysis

We used TDA to systematically quantify the *structure* of the sampled response surfaces, with the use of a persistence diagram (Chazal and Michel, 2017) for the top 5% quantile of NPE values. This tool efficiently computes the number of local optima and analyzes the noise along the surface. This is done by scanning the response surface by decreasing NPE values and keeping track of the NPE value at which a new local optimum cluster emerges (birth) and later merges with surrounding clusters (death). Clusters displaying large differences between birth and death (points located far from the 1:1 line in the persistence diagram) represent significant structures (i.e., local optima). In contrast, clusters displaying small differences between birth and death (points located close to the 1:1 line in the persistence diagram) indicate noise in the surface. This tool is particularly helpful in higher dimensions where visual analysis is impossible. A 1D example is given in Figure 6.

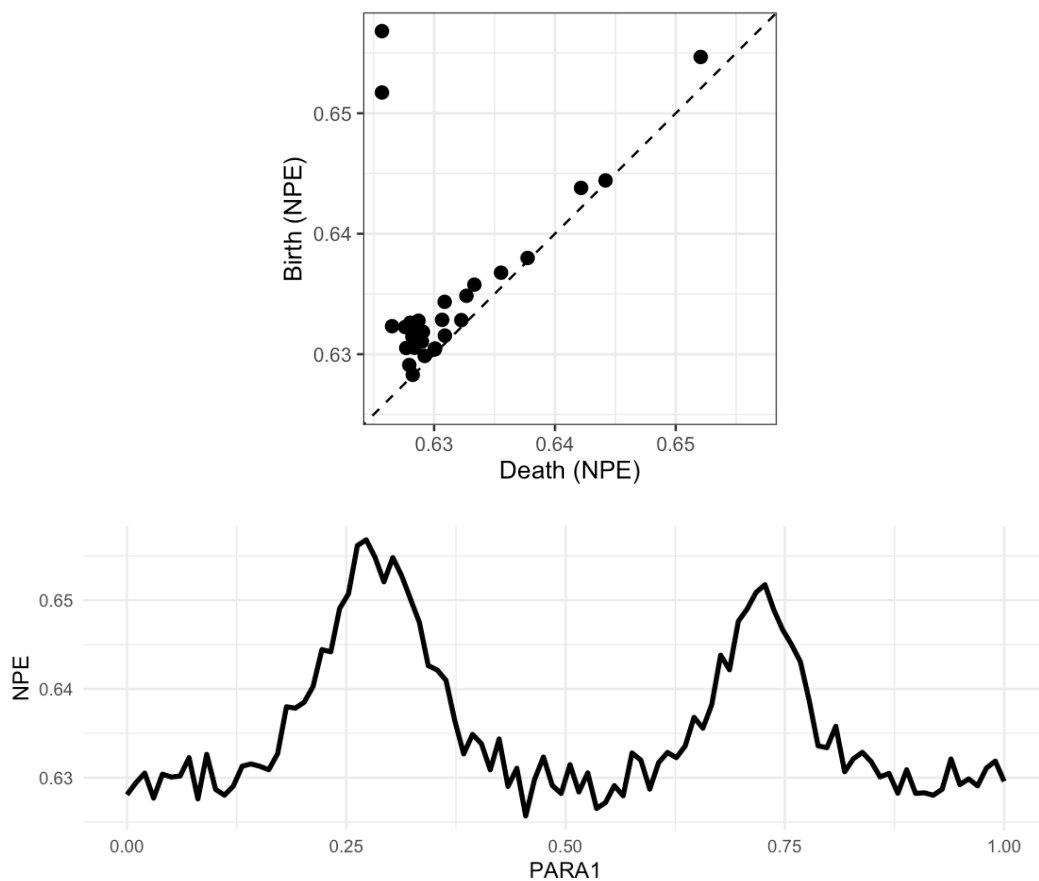


Figure 6: Example of a topological data analysis with persistence diagram (top) of a 1D response surface (bottom). The given response surface displays one global optimum, another local optimum (top left two points with a comparably large difference between birth and death of the clusters in the persistence diagram) and noise around them (multiple points along the 1:1 line indicating small persistence). Most of the noise is concentrated between NPE values of 0.625 and 0.635, as shown by the lower-left dense point distribution in the persistence diagram.

Genetic Algorithm Analysis and Population Dynamics

Once the 4D-volumes were created and homogenously sampled, we performed 10 GA calibrations on these mapped surfaces. Even though the mapping of the 4D-volumes used to analyze the *landscape structure* is discrete, the GA was run in its original continuous version in HBV-light throughout the first part of the thesis. We kept track of the GA evolution at the end of each generation, saving both the best value and all the population members' position in the 4D-volume. For a visual representation of the results, we computed a 3D projection of each 4D-volume, with highlighted high-performance NPE zones (top 0.1% quantile). We always chose the three most influential parameters of the given 4D-volume to create the projection. Alongside, we also plotted the GA paths of the best member at each generation. This provided a view of which of the different zones were getting explored and which ones were not. Generally, a 3D projection of a 4D space can produce visual bias: some high-performance regions may visually appear as one cluster but are actually separate zones. We therefore used TDA to check whether the high-performance zones truly formed a single cluster, when visually represented so. For simplification reasons, we normalized (i.e., rescaled to $[0; 1]$) all parameter ranges in these 3D visualizations.

To understand and explain the GA trajectory, especially in cases where the GA gave sub-optimal results, we calculated the ratio of values above an NPE threshold (i.e., top 0.5% quantile values) for each slice of the 4D-volumes. This ratio represents the probability of finding a new high-performing parameter set at each slice. This ratio was then directly compared to the best NPE value at each precise slice. This enabled us to understand what volume and shape these high-performance clusters form. Furthermore, we computed a histogram of the number of GA population members located within each slice for different calibration milestones: 50 runs (corresponding to the first generation), 1,000 runs, 5,000 runs, and 10,000 runs. This allowed us to test if and how long the diversity was kept among the GA members, or if the GA converged prematurely to a (sub-optimal) solution. Altogether, these analyses enabled us to understand how the GA scans the parameter space and which kind of high-performance clusters it aims for.

Results

Sobol Analysis

The results of the Sobol analysis presented in the [Appendix I](#) show that each catchment has a distinct influence ranking for the parameters, reflecting geographical realities. Generally, the first-order indices ranking matches the total-order indices ranking relatively well. However, this is not always the case for single parameters, indicating highly interactive behaviors with equifinality potential. While the minimum total-order index values for each catchment are all nearly zero (indicating a parameter without influence), the maximum total-order index values vary greatly among catchments, ranging from 0.3 (parameter SFCF in catchment 5014) to 0.95 (parameter BETA in catchment ES000356). Also, the number of influencing parameters is highly variable among catchments. Some catchments display one highly influential parameter, with all other parameters practically not contributing to output variance (e.g., catchment 2403). In contrast, other catchments display a more gradual influence decrease with low-ranked parameters still displaying a substantial output variance (e.g., catchment 5014).

Landscape Structure of the 4D-Volumes

The 4D-volumes created and sampled based on the Sobol analysis show very complex *landscape structures* that are unique for each catchment and 4D-volume. The 3D projections of the volumes, combined with the persistence diagram of the TDA and the corresponding NPE values are displayed in the [Appendix II](#). Interestingly, both the near-optimum *landscape* (parameters fixed at 10,000 runs) and the *landscape* during exploration (parameters fixed at 3,500 runs) display very similar *structures* and characteristics in all cases, despite NPE values sometimes differing strongly. This indicates that there is no need to differentiate the two scenarios for the analysis, when analyzing the exploratory capacity of the GA.

The results of the TDA indicate that some catchments present a highly noisy response surface, while others are smooth in the gridded space. 70 of the 84 4D-volumes present one single global optimum (one clearly defined high-performance cluster). This global optimum varies greatly in shape. Some 4D-volumes display a relatively “round” high-performance cluster (e.g., 5014_4D_D) while others present a layered (flat) high-performance

zone (e.g., 2403_4D_J, ES000356_4D_J), with one or two parameter slices containing all highest NPE values. Other shapes can be observed in the [Appendix II](#). Besides this, the following 14 4D-volumes present two high-performance local optima: 2426_4D_A, 2426_4D_J, 5014_4D_J, CZ000098_4D_A, DEBB0132_D, DEBB0136_D, ES000356_A (and their corresponding near-optimum 4D-volumes). These multimodal 4D-volumes all come from catchments displaying larger KGE ranges in [Table 2](#).

Exploratory Capacity of the Genetic Algorithm

When performing a GA calibration of the 4D space, the parameter sets selected generally reach high-performance zones quickly. After only 1,000 runs (corresponding to the 20th generation), in about 70 out of 84 cases parameter sets are already very close to their final position and their NPE value does not improve significantly anymore. This is for example the case for the 4D-volume 2403_4D_B, shown in [Figure 7](#) and [Table 4](#). Nevertheless, the GA calibrations also show different behaviors in the 14 remaining cases. Here, the different calibration outputs do not converge to the same final position and / or do not concentrate around the best NPE value of the 4D-volume. This sometimes leads to a much lower NPE output value (e.g., 2403_4D_E in [Figure 8](#), with an NPE value of 0.36 found for Calibration 9 instead of 0.63 for the best NPE values of the 4D-volume). Interestingly, both the ideal case presented in [Figure 7](#) and the problematic case presented in [Figure 8](#) come from the same catchment (i.e., both cases come from different 4D reductions of the same catchment). Furthermore, for multi-optima 4D-volumes, the different local optima are not systematically identified and explored when calibrating multiple times, as shown in [Figure 9](#) for the 4D-volume 2426_4D_A. For a more detailed insight, all the 84 4D-volumes including GA paths are displayed in the [Appendix II](#).

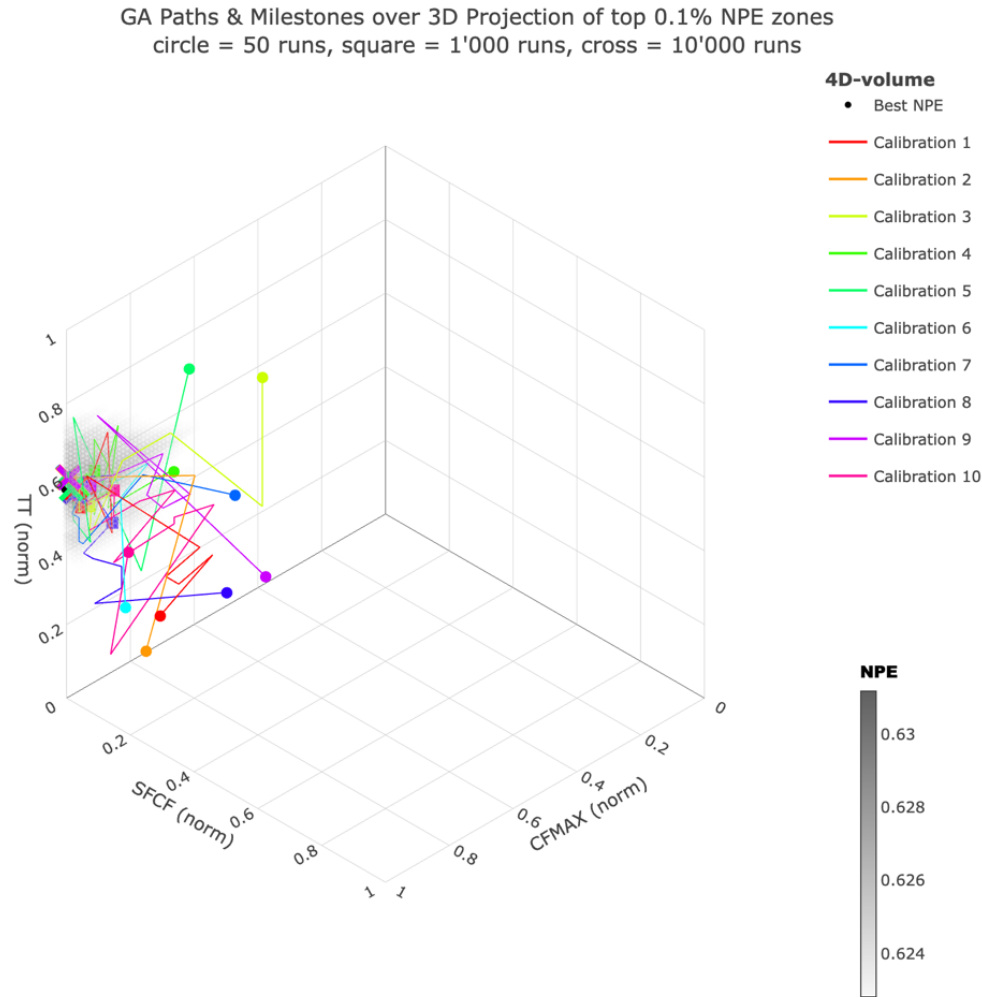


Table 4: NPE values of 10 different GA calibrations for the 4D-volume of the four most influential parameters of catchment 2403 (2403_4D_B, corresponding to Figure 7) at different milestones: 1,000 runs (corresponding to the 20th generation), 3,000 runs, 5,000 runs and 10,000 runs (corresponding to the 200th and final generation). NPE_best represents the best NPE value of the 4D-volume. After only 1,000 runs, the NPE value does not improve significantly anymore in this case.

CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.62774407	0.63015189	0.63070356	0.63117055	0.63117353
2	0.63048346	0.63115921	0.63131741	0.63132689	0.63117353
3	0.62595794	0.63088432	0.63110146	0.63115593	0.63117353
4	0.62896098	0.63086961	0.63116254	0.6311884	0.63117353
5	0.63086973	0.63109887	0.63111179	0.6311607	0.63117353
6	0.63000448	0.63105469	0.63105469	0.63118182	0.63117353
7	0.63058876	0.63098479	0.63130382	0.63137484	0.63117353
8	0.62465011	0.63104745	0.63104745	0.63105179	0.63117353
9	0.62879043	0.63073068	0.63090108	0.63117555	0.63117353
10	0.62618856	0.63082451	0.6308862	0.63129962	0.63117353

Figure 7: 4D-volume of the four most influential parameters of catchment 2403 (2403_4D_B). The GA paths are shown for 10 different calibrations. For each calibration, the GA quickly converge to the best NPE value of the 4D-volume: after selecting the first generation randomly (50 runs – circle), the GA is already very close to its final position after only 1,000 runs (square). The cross represents the final position after 10,000 runs.

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs

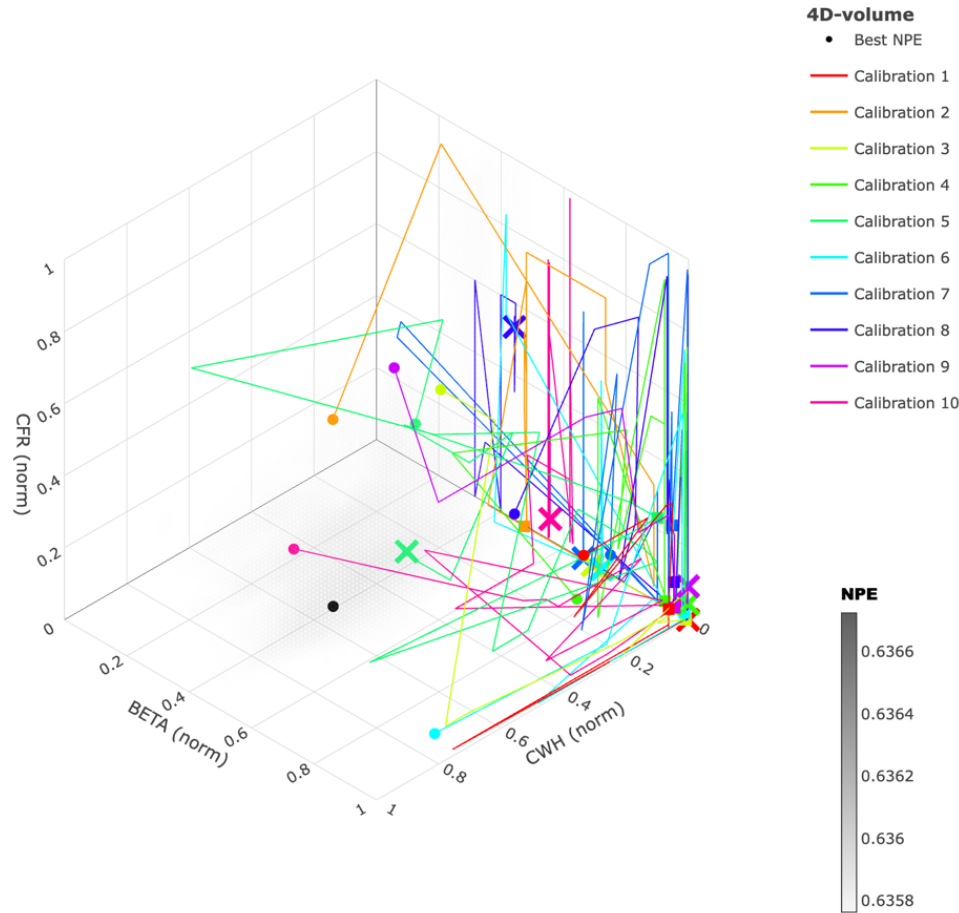


Figure 8: 4D-volume of four parameters of catchment 2403 (2403_4D_E). The GA paths are shown for 10 different calibrations. The outputs of the different calibrations do not cluster together and do not converge to the best NPE value of the 4D-volume.

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs

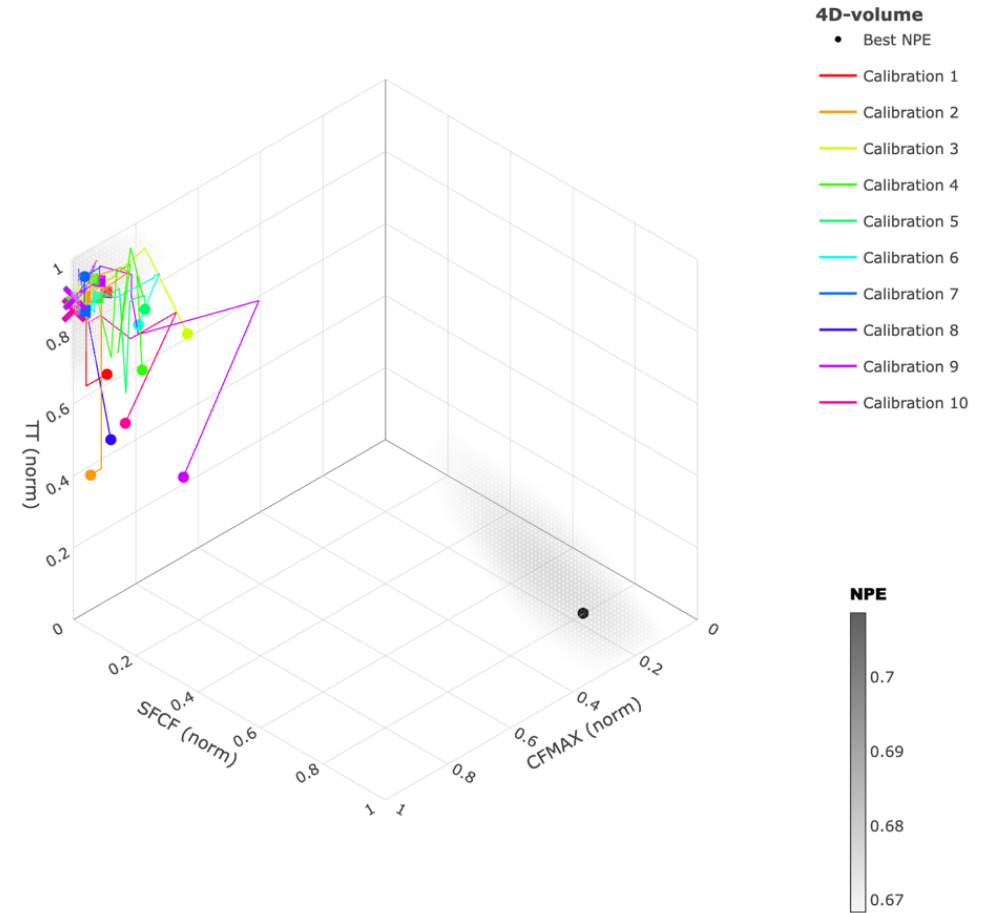


Figure 9: Multi-optima 4D-volume of the four most influential parameters of catchment 2426 (2426_4D_A). The GA paths are shown for 10 different calibrations. The outputs of the different calibrations do cluster together, but they do not converge to the best NPE value of the 4D-volume, letting the global optimum cluster completely unexplored.

Probabilistic Mechanism of the Genetic Algorithm

The partly problematic behavior of the GA was analyzed by locating the position of each GA population member during calibration. The results, presented visually in [Figure 10](#) for the problematic calibration of [Figure 9](#), show that all population members rapidly

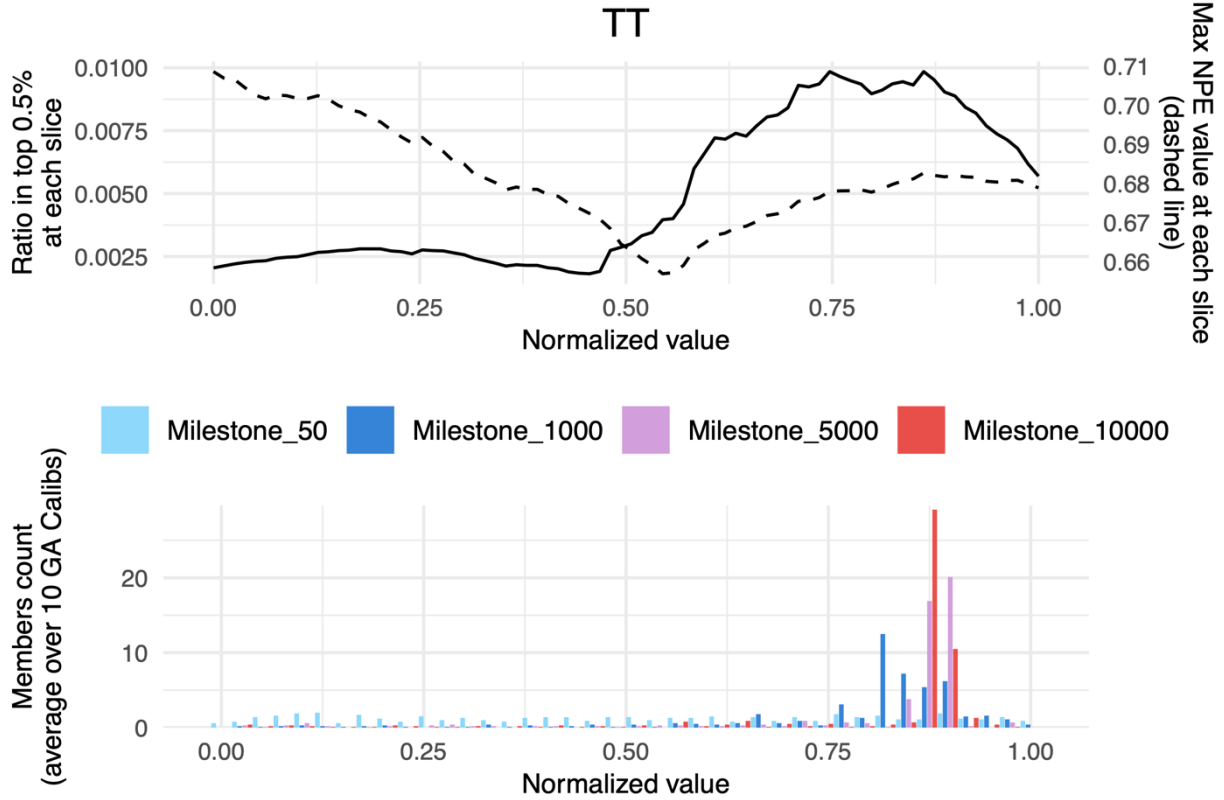


Figure 10: **Top:** Representation of TT slices of the 4D-volume 2426_4D_A (displayed in [Figure 9](#)). I.e., behind each of these discrete 80 TT values, there is a 3D-cube containing all combinations of the three remaining parameters (i.e., SFCE, CFMAX and K2). The figure shows the best NPE value at each TT slice (dashed line) and the probability of finding a new high-performing parameter set at each slice (i.e., a parameter set that belongs to the top 0.5% quantile of the whole gridded 4D-volume; full line). Results show that the best performing parameter set of the whole 4D-volume is located at a value of TT = 0 (in normalized space). Results also show that the probability of finding a new high-performing parameter set is generally very low (for a given mutation, 0.01 at the highest), and that this probability is highest for TT = 0.75 and 0.85 (i.e., these local optima are larger in volume than the global optimum at the slice TT = 0). This explains why all population members rapidly converge towards these slices. **Bottom:** histogram displaying the position and count of the GA population members after a given number of runs. At Milestone_50 (50 runs – first generation), the members are located homogenously among individual TT slices as the generation is created randomly. At Milestone_1000 (1,000 runs – 20th generation), most of the members have already converged towards the previously discussed TT slices. Finally, at Milestone_10000 (10,000 runs – final generation), the diversity is strongly reduced and the cluster displaying the highest performance (inside the slice TT = 0) has not been explored. The results are similar when analyzing the slices of the remaining three parameters of the same 4D-volume. These coverage plots, available for the Swiss catchments, are displayed in the [Appendix III](#).

converge towards one local optimum, rather than exploring the whole parameter space fully. The capacity of the GA to jump between high-performance clusters is very limited, as GA member diversity rapidly declines. By computing the probability of finding a new high-performing parameter set, the results show that the GA aims for the largest volume of relatively well performing NPE cluster instead of aiming for the best NPE cluster (or even more adequately: aiming for *all* well performing clusters one after the other). In other words, regions with higher sampling probability dominate the search, even if they do not contain the global optimum.

Discussion

Equifinal Behaviors

When reducing the dimensionality of the problem to 4D, equifinality can still be observed: certain 4D-volume display a large subset of parameter combinations yielding equally valid results. These parameter sets are sometimes located far from each other in the parameter space, confirming previous studies (Beven and Freer, 2001). In some cases, the interaction between parameters is obvious. The 4D-volume 2426_4D_A (Figure 9) presents interactions between parameters TT, CFMAX and SFCF (see Table 1 for a precise description of the parameters). These three parameters are related to snow processes. For higher values of TT, more precipitation falls as snow in the model. To reach identical water flow quantities, the snow must melt quicker for the water to be directly reinjected into the active hydrological system. This is done by compensating with a larger CFMAX value, increasing the degree-day melt factor. This typical compensation mechanism, adjusted and fine-tuned with SFCF (to adjust for snow storage quantities), creates two distinct high-performance NPE clusters. Another straight-forward compensation example is the interaction between parameters related to evapotranspiration and soil processes (i.e., BETA, LP and FC). For higher values of FC, more water can be stored in the soil in the model. To reach identical runoff quantities, less water must be removed by evapotranspiration so that the larger soil reservoir can still fill and transmit water to groundwater and discharge. This is done by compensating with a larger LP value to directly reduce evaporative losses. Another compensation mechanism can arise through decrease of the shape coefficient BETA, which controls the proportion of precipitation and meltwater that reaches the groundwater for a given soil moisture content. This second mechanism can be observed in the 4D-volume CZ000098_4D_A (see Appendix II). In other cases, the interaction between parameters is less intuitive. Or a combination of compensation-prone parameters does not create the expected equifinal behavior (e.g., TT, CFMAX and SFCF in 2403_4D_B in Figure 7).

For the Swiss catchments (i.e., catchments 2155, 2403, 2426 and 5014), the parameter K2 seems to present a compensation mechanism on its own. Indeed, most complicated response surfaces are linked to this parameter. Furthermore, even when the persistence

diagrams of parameter spaces containing K2 show a unimodal *structure* in the top 5% quantile of NPE values, the clustering of the GA calibrations hints at a secondary local optimum outside this top 5% quantile. This can be observed, e.g., for catchment 2403 (Figure 8; K2 being the fourth parameter) or for the parameter space 2426_4D_J in Figure 11.

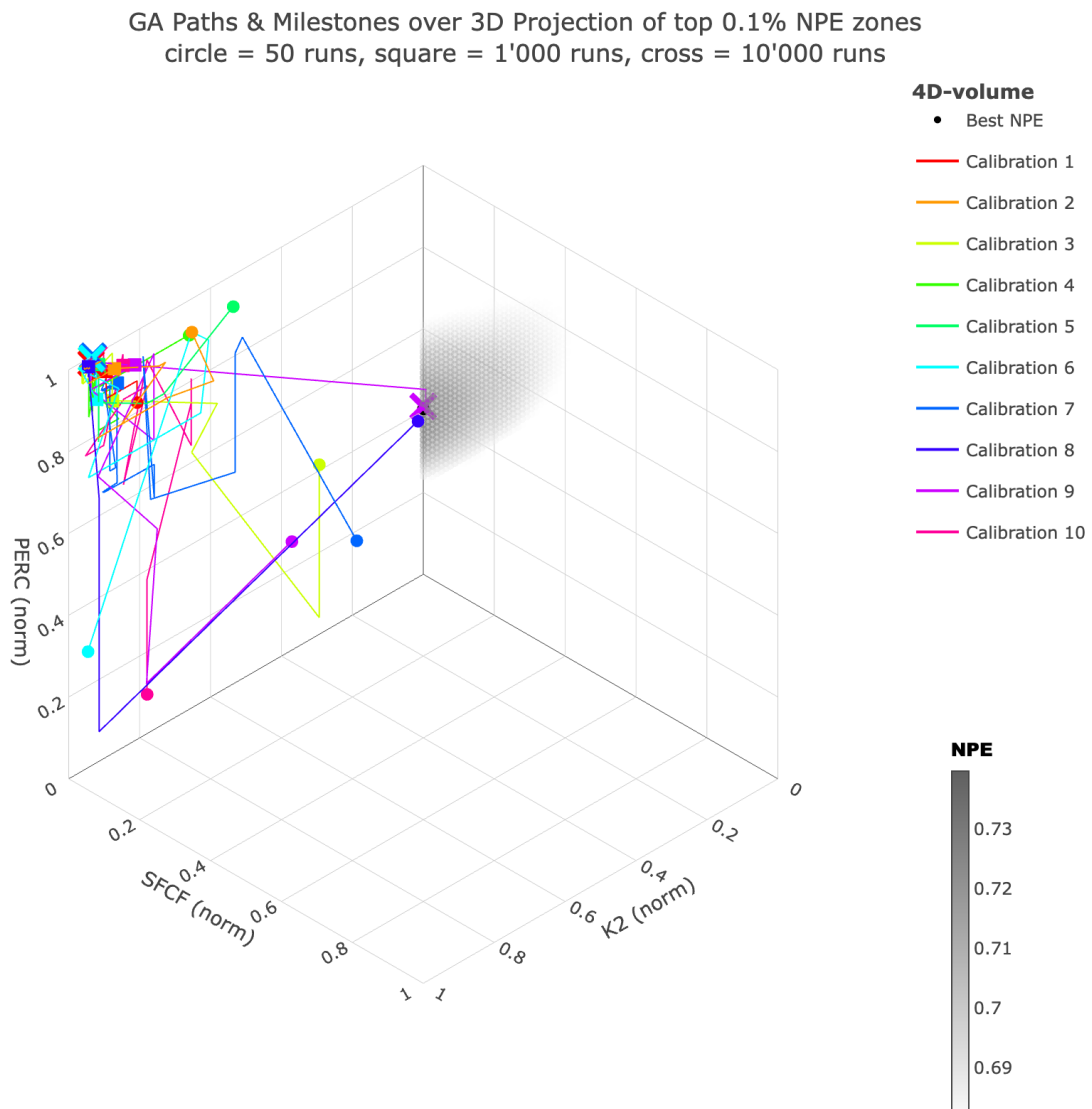


Figure 11: 4D-volume of four parameters of catchment 2426 (2426_4D_J). The GA paths are shown for 10 different calibrations. The outputs of the different calibrations cluster together outside the global optimum zone, hinting at a secondary local optimum caused by the compensation mechanism of the parameter K2.

This compensation mechanism can be explained as follows: water flowing from a highly filled lower storage (baseflow) with a low K2 value can produce a similar outflow as water from a nearly empty lower storage with a high K2 value. In other words, this leads to two different system states that generate comparable runoff. This process is purely

theoretical and does not reflect the geographical reality on the field, i.e., both states are equally valid for the model. This phenomenon is further amplified by the dual role of $K2$ during model calibration: When the objective function is computed for an HBV simulation with a given parameter set, the lower storage is initially filled inversely proportional to the value of $K2$. This approach is used because the model's warm-up period is often too short to properly fill the lower storage when starting from an empty reservoir. Without this adjustment, the storage would remain unrealistically low at the beginning of the simulation, which would negatively affect the calibration results. But this initialization leads to the model starting closer to a potential equilibrium state. This $K2$ -linked multimodal behavior, illustrated in [Figure 12](#), does not seem to appear for the European catchments and their smaller $K2$ range (see [Table 1](#)).

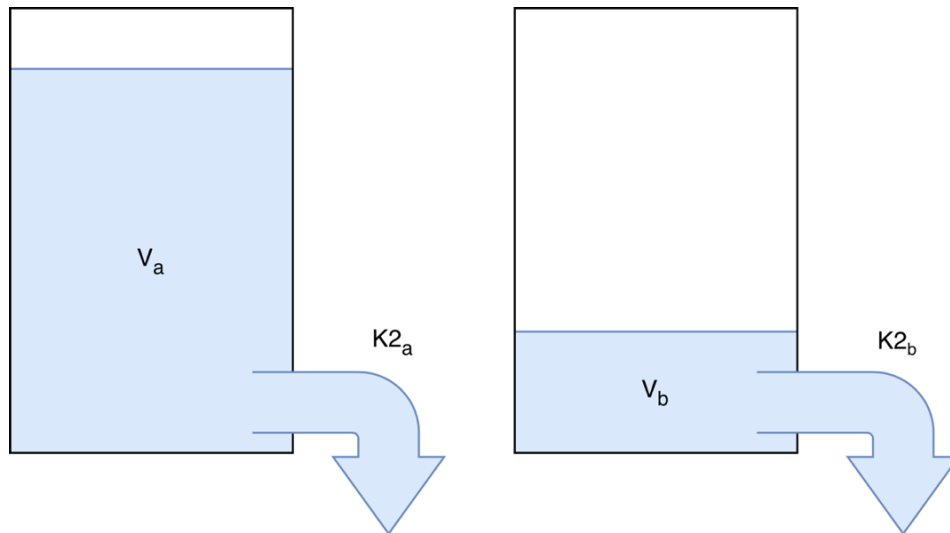


Figure 12: The same quantity of water flows from the lower storage with different $K2$ values, depending on the volume of water stored in this reservoir (i.e., $V_a * K2_a = V_b * K2_b$ for a certain value of $K2_a < K2_b$).

Additionally, high-performance clusters are very often situated at the edge of at least one parameter range in the 4D-volumes. This also highlights model compensation strategies with the optimal parameter sets possibly situated outside the analyzed 4D-volume. In certain cases, this is an attempt made by the model to modify the water balance by adding an additional path for water to enter or leave the catchment ([Clerc-Schwarzenbach et al., 2026](#)). This observation, in addition to the behavior of $K2$, is highly valuable when setting the parameter ranges. However, the present thesis focuses on the exploratory capacity of the GA on a *given landscape structure*. Since the thesis does not aim at increasing

absolute NPE values, this observation is not analyzed in further detail here. Generally, the analysis of these compensation mechanisms goes beyond the scope of this thesis, but the presence of equifinal behaviors, also in the reduced 4D space, validates the methods of the thesis.

Gridded Landscape Structure

One important point to discuss is the validity of the discrete gridded 4D *landscape structure* and more precisely if it represents adequately the continuous reality of the parameter space. Because of the infinitely small volume of each grid point, most of the parameter space is not being mapped in the current setting. The possibility that the gridded observed *structure* does not represent the *true* response surface is not to be ignored. Indeed, NPE values in-between the lattice points could theoretically be totally different than their closest nodes. This would imply a very noisy and irregular *true* response surface. Nevertheless, the fact that both the near-optimum *landscape* (i.e., nine unvaried parameters fixed at 10,000 runs) and the *landscape* during exploration (i.e., nine unvaried parameters fixed at 3,500 runs) display very similar *structures* and characteristics makes this possibility rather unlikely. The probability of the regular lattice revealing similar features in both cases would be almost nonexistent if the response surface was completely irregular. It is true that NPE values of the GA calibrations are sometimes higher than the best value of the gridded space (e.g., 4D-volume 2403_4D_A presented in [Table 4](#)), hinting at the issue. But the values remain very close, indicating a rather stable surface in-between the grid points.

Extrapolation into the Full Dimensionality

An extrapolation of how a 13D *landscape structure* might look seems extremely hazardous. Indeed, the Sobol indices ranking does not predict which 4D-volumes show more complex or simpler response surfaces: regularly, the four most influential parameters create a simpler *landscape structure* than parameters ranked fifth to eighth (e.g., catchment 2403). The Sobol ranking is based solely on the output variance, with the first parameter groups always displaying larger NPE ranges throughout their 4D-volumes. This is independent of the characteristics of the *structure*. A possible extrapolation could be that 13D *landscapes* resemble their 4D-volume containing the parameter K2, as this

parameter seems central in creating multiple local optima. This is partly supported by the *structures* of the Sobol groupings J and K (i.e., combining highly influential and less influential parameters; see [Table 3](#)) resembling the *structures* of the Sobol groupings containing K2 within the same catchment (e.g., catchment 2426). Nevertheless, this is highly speculative, and new interactions could arise when combining 13 parameters. These added interactions could possibly completely modify the *structure* of the parameter space when increasing the dimensionality from 4D to 13D. Even if this point is discussed deeper in the [Second Part](#) of the thesis, further research is required to describe how reduced parameter spaces are related to the full dimensional response surface.

Exploratory Capacity of the Genetic Algorithm

Generally, the GA performs well in many 4D cases, especially when the response surface is simpler (i.e., unimodal). In contrast, for more complex *landscape structures*, the exploratory capacity of the GA is strongly reduced. High-performance NPE clusters are not systematically detected when performing multiple calibrations of the same reduced space. Thus, NPE values of the selected parameter sets are sometimes significantly lower than those present in the response surface. Arguably, this thesis focuses on complex cases with catchments being specifically selected for such behaviors. Therefore, the experimental setting likely does not fully reflect the capabilities of the GA in a general 4D parameter space. This assumption is confirmed by the following observation: the catchments selected for lower KGE ranges (see [Table 2](#)) all obtain very good GA exploratory results. Nevertheless, these catchments all display simple 4D response surfaces with a clearly defined global optima. As speculated previously, 13D *landscape structures* might present highlighted interactions among parameters and resemble more problematic 4D-volumes. For this reason, precisely understanding how the GA proceeds, and why certain high-performance clusters are not detected is essential, especially when trying to modify and optimize the GA in a later step.

Diversity Loss among Genetic Algorithm Members

By design, the GA recombines parameter sets by spreading and exchanging single parameter values of well-performing members. The parameter values of poorly performing members within a generation are unlikely to be picked for recombination, as best-

performing members have higher probabilities of being selected. As a result, some parameter values gradually disappear from the pool of available values for a single parameter. In contrast, the frequency of other single parameter values increases as better-performing members spread their parameter values. Mutation is the only process that injects new single parameter values into the available pool. This mechanism represents the strength of the GA: favoring parameter values of well-performing members, while still exploring further the parameter space by injecting new values through mutation.

The limitation of this GA design is that the diversity at each single parameter declines very quickly with only a few single parameter values surviving. Mutations should provide new values, but after a few generations only, the probability of a new parameter value creating a new better performing member is very low. This new parameter value therefore disappears quickly from the pool most of the time (this mimics biological evolution rather accurately). This means that after a strong initial increase in NPE values, the performance of the GA quickly flattens, and better-performing parameter sets are found less frequently. The real problem arises when the probability of creating a new strong member through mutation is biased by cluster sizes (i.e., when the best performance zone is very small). This prevents high-performance NPE clusters from being detected by the GA, as visually presented in [Figures 9 and 10](#).

Limitations of the Genetic Algorithm and Outlook

Generally, the GA design shows two problems: firstly, it converges rapidly to a high-performance region, but then many runs (generations) almost do not bring any added value; secondly, the diversity loss prevents finding different high-performance zones efficiently. The analysis also shows that the GA cannot probabilistically find sharp (i.e., low volume) peaks in the response surface.

The diversity loss problem is well-known and well documented for GAs ([Katoch et al., 2021](#)). An intuitive solution to fix these issues would be to increase the probability of mutation. The experiment was already conducted specifically for HBV parameter optimization. However, it was concluded that the current mutation rate produces the best results ([Seibert, 2000](#)). Another solution that has not been tested for HBV is to prevent spatially close members to be recombined together ([Eshelman and Schaffer, 1991](#)). But the most

used strategy to overcome the problem is to set regular GA restarts to escape a local optimum (Dao et al., 2015; Fukunaga, 1998; Sultana et al., 2025). Interestingly, and even though diversity loss is recognized as the major problematic factor, the previously cited modified GAs do not use a diversity collapse metric to trigger restarts. Restarts are mainly based on a fitness stagnation criterium. These two concepts are related but not identical. Fitness stagnation does not necessarily mean that diversity has collapsed. In some *landscapes*, the population may temporarily stop improving even though diversity is still present. In such cases, a restart may be undesirable, as the population may still contain promising genetic material. New and useful combinations can still emerge, but they may require more time because their probability of appearing is low. This stagnation restart strategy is indirectly tested in the current thesis by calibrating the parameters 10 times. However, the probability issues discussed previously rapidly bring the newly started GA into the same zone and low volume high-performance clusters remain undetected. For the current HBV parameter optimization problem, an interesting possible solution that was tested in the **Second Part** of this thesis is to trigger the GA restarts based on a diversity threshold, and to exclude visited zones at restart to force the GA into new regions.

Second Part: Improvement of the Genetic Algorithm

Data and Methods

Design of the Modified Genetic Algorithm

The modified GA tested in the second part of the thesis is based on the standard GA analyzed in the [First Part](#), with several changes introduced to reduce the population diversity loss during the search process:

- **Restart based on diversity collapse:** The modified GA is restarted whenever the population diversity falls below a given spread threshold. The diversity is measured using a Minimum Spanning Tree (MST) built from the population. The MST score of the initial generation is used as a reference. During the calibration process, if the spread falls below a fixed percentage of this initial score, a restart is triggered. The percentage is defined within the calibration settings. The MST is computed in normalized space to keep logical distance relations between parameters, as their respective calibration range varies greatly and spans over different scales.
- **Removal of over-explored regions:** In the generation just before a restart, the position of all members is examined along each parameter axis. The members are grouped into bins, with the number of bins defined within the calibration settings. Any bin containing more than a certain percentage of the population is removed from the search space. The percentage is defined within the calibration settings. This zones removal prevents the modified GA from repeatedly searching the same regions.
- **Keeping the best member without recombination possibility:** At each restart, the best member from the previous generation (i.e. the elite member) is compared with the newly randomly generated population. If this elite has a better fitness score (i.e., a higher NPE value) than every member of the new generation, it is kept in the population and replaces the member with the lowest fitness score. However, the elite is not allowed to recombine and spread its genes for the rest of the calibration process, ensuring that the GA does not converge toward this solution

again. This allows good solutions from different regions of the parameter space to be preserved, despite the removal of over-explored zones.

Table 5 shows the new variables added to the modified GA. With these modifications, the final GA generation is expected to contain several high-performing parameter sets located in different areas of the parameter space, rather than converging into a single zone. The final version of the modified GA implemented into HBV-light also contains the possibility of a discrete calibration process.

Table 5 : Summary of the variables added to the modified GA.

Variable	Definition
SpreadRatioMin	Ratio threshold used to trigger a GA restart, defined by comparing the MST of each generation to the reference MST computed for the first generation.
NrOfBins	Number of bins per parameter used to divide the GA population, to count members per bin, and to potentially remove space at each GA restart.
TopMassFrac	Ratio threshold used to remove bins at a GA restart, defined by the proportion of population members present in each bin.
Discrete	Setting if the parameter space search is discrete or continuous.
NrOfValues	Number of equally spaced discrete values per parameter for a discrete calibration process.

After briefly testing different variable values for the modified GA, we conducted the analysis with the values presented in Table 6. These values display a representative and stable behavior for the different catchments, as presented in the following paragraph specifically for the variable SpreadRatioMin.

Table 6: Variable values used for the analysis of the modified GA.

Variable	Analysis in 4D		Analysis in 13D	
	modified GA (continuous)	modified GA (discrete)	modified GA (continuous)	modified GA (discrete)
SpreadRatioMin	0.5	0.5	0.7	0.7
NrOfBins	100	80	100	80
TopMassFrac	0.5	0.5	0.7	0.7
Discrete	false	true	false	true
NrOfValues	-	80	-	80

The variable SpreadRatioMin indicates when the member diversity triggers GA restarts. Analyzing how this diversity evolves for a calibration of the basic GA is essential to ensure that restarts are happening at a meaningful timing when selecting the value of this variable. In the full dimension (13D), the median of the spread score (i.e., the MST score representing current member diversity) at the first randomly selected generation is slightly above a value of 40 for the European catchments (see [Figure 13](#)). The value for the Swiss catchments is slightly higher due to the different selected parameter ranges presented in [Table 1](#). This reference spread score does not vary much among European catchments, given the consistent parameter ranges among calibrations. The median of the spread score for the European catchments quickly decreases and stagnates at a value of about 23 after a few generations. This means that the variable SpreadRatioMin must have a minimum value of $23 / 40 = 0.58$ to be able to trigger restarts. Nevertheless, depending on the *landscape structure*, this stagnation value can vary greatly and be much larger for individual catchments (e.g., catchment ES000356). Also, because of the randomness of the GA process, individual calibrations of the same catchment display very different spread score evolutions. For these reasons, we selected a SpreadRatioMin value of 0.7 in this analysis, ensuring the restart routine is effectively activated for all catchments. We followed the same procedure in 4D, leading to the values presented in [Table 6](#).

Altogether, we tested three new versions of the GA. We compared these new versions with the basic version of the GA analyzed in the [First Part](#) of the thesis. These GA versions are presented in [Table 7](#).

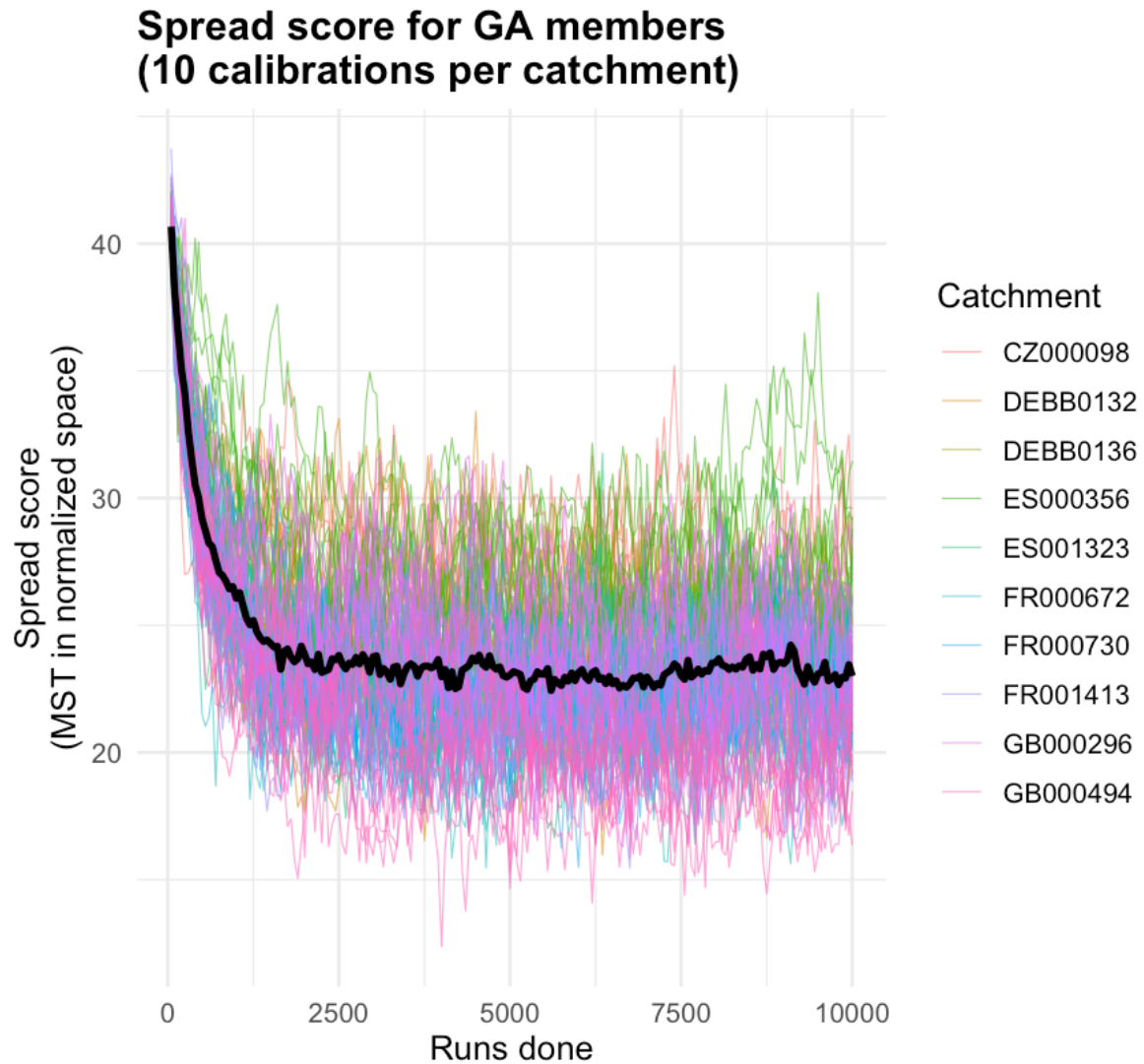


Figure 13: Evolution of the spread score (Minimum Spanning Tree MST) during full dimension (13D) calibration (basic GA) of the European catchments. The black line represents the median. The median value at the first randomly selected generation is slightly above a value of 40. The median then quickly decreases and stagnates at a value of about 23 after a few generations. Therefore, the variable *SpreadRatioMin* (see [Tables 5 and 6](#)) must have a minimum value of $23 / 40 = 0.58$ to be able to trigger restarts.

Table 7: GA versions analyzed and compared in the thesis. Three new versions of the GA were tested and compared with the basic version of the GA analyzed in the [First Part](#) of the thesis.

GA version	Definition
Basic GA (continuous)	Standard version of the GA used in HBV-light (Seibert, 2000) and analyzed in the First Part
Basic GA (new discrete version)	Discretized version of the standard GA
Modified GA (continuous)	Continuous version of the newly developed GA
Modified GA (discrete)	Discretized version of the newly developed GA

Analysis of the Behavior of the Modified Genetic Algorithm in 4D and 13D

To test the abilities of the different versions of the GA, we compared the outputs of the modified GA with the outputs of the basic GA using following metrics for 10 calibrations:

- NPE value
- NPE range among calibration outputs
- Spread score: MST of calibration outputs (to be differentiated from the internal MST score among population members of a single calibration used to trigger a restart; see Figure 14).

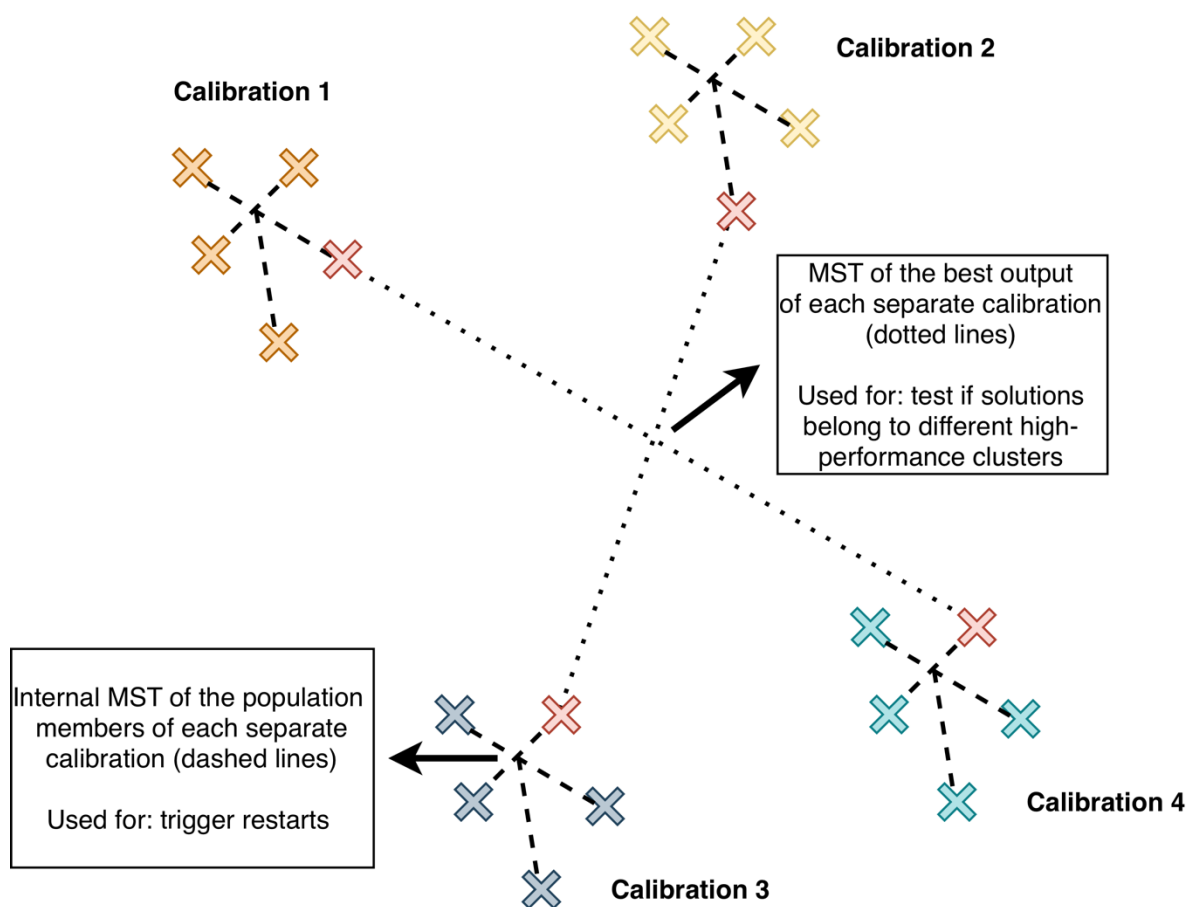


Figure 14: Schematic representation of the difference between the internal MST of the population members of each separate calibration and the MST of the best output of each separate calibration (red crosses).

Optimal results imply reaching the highest possible NPE values and displaying a small NPE range between individual calibration outputs. As opposed, a large NPE range means that the GA sometimes remains stuck in suboptimal local maxima. Furthermore, when the NPE range is kept small, a large spread score among calibration outputs is desired. Indeed, this ensures that these individual outputs belong to different high-performance

clusters (if they exist), reaching the purpose of the modified GA to detect alternative optima.

In 4D, we conducted the analysis using a subset of the 4D-volumes presented in the [First Part](#) of the thesis. Specifically, we used the Swiss catchments selection presented in [Table 2](#), i.e., catchments 2155, 2403, 2426 and 5014, as those showed the most problematic behaviors. In 13D, we used all the catchments presented in [Table 2](#).

Next, because of the dual role of the parameter K2 discussed in the [First Part](#), we analyzed the K2 output values of the 10 individual calibrations in the full dimensionality (13D), including corresponding NPE values. This allowed us to concretely assess if different high-performance clusters can be found along this parameter (i.e., if the modified GA finds more or different local optima along this parameter compared to the basic GA).

Results

4D Analysis

The results show that the **discrete version of the modified GA** displays an interesting behavior. For a few specific cases containing two local optima, it is the only version of the GA that reaches the global optimum of the 4D-volume almost constantly (e.g., 4D-volume 2426_4D_A presented in [Figures 15 and 16](#)). More interestingly, it does so after detecting the other local optimum in which the other versions of the GA remain stuck.

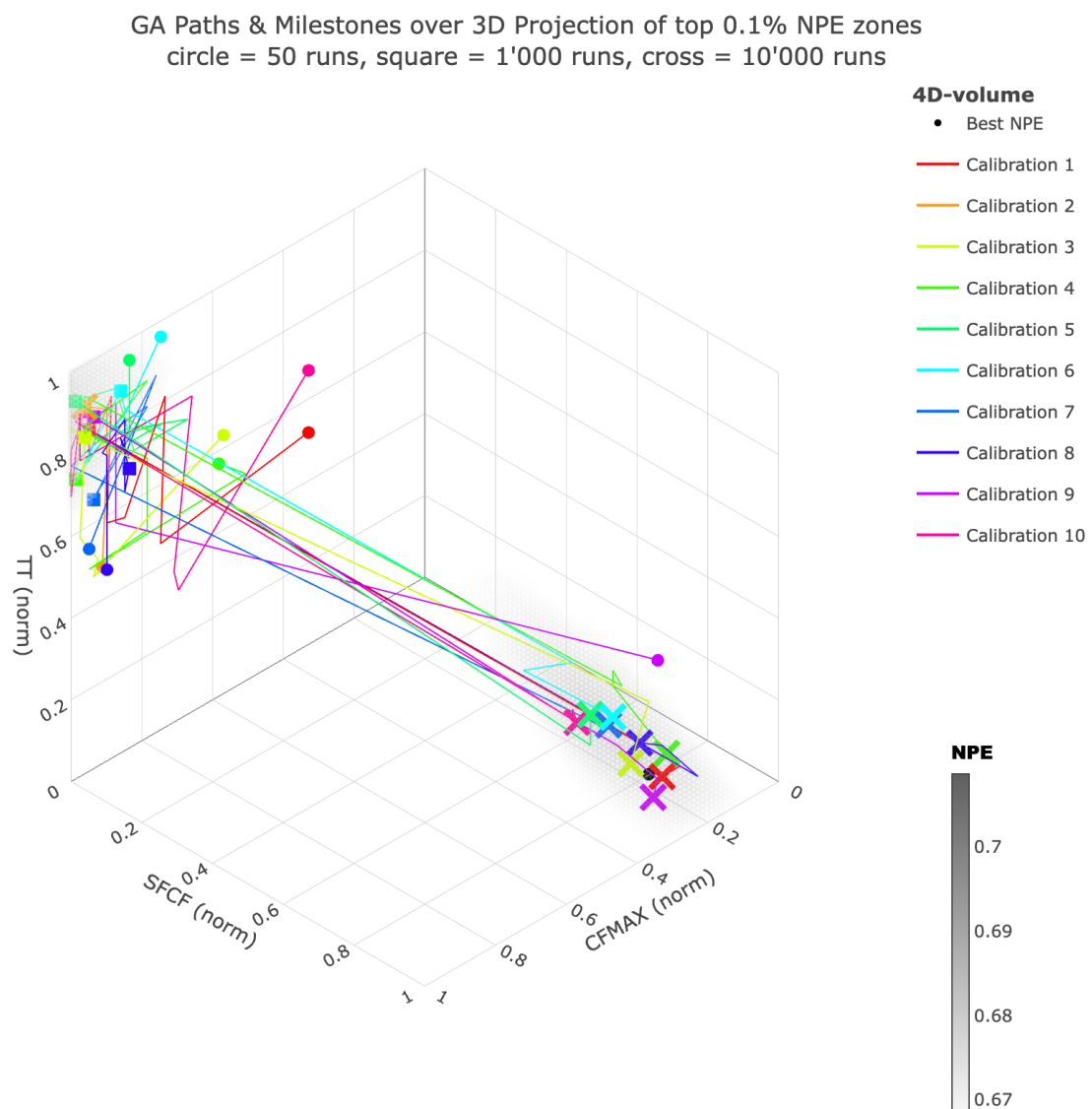


Figure 15: 4D-volume of four parameters of catchment 2426 (2426_4D_A). The GA paths are shown for 10 different calibrations of the modified GA (discrete). This version of the GA is the only one almost constantly reaching the global optimum of the 4D-volume. More interestingly, it does so after visiting the other local optimum in which the other versions of the GA remain stuck. See [Figure 9](#) for a comparison with the basic GA.

2426: GA_4D_A (10 GA Calibrations)

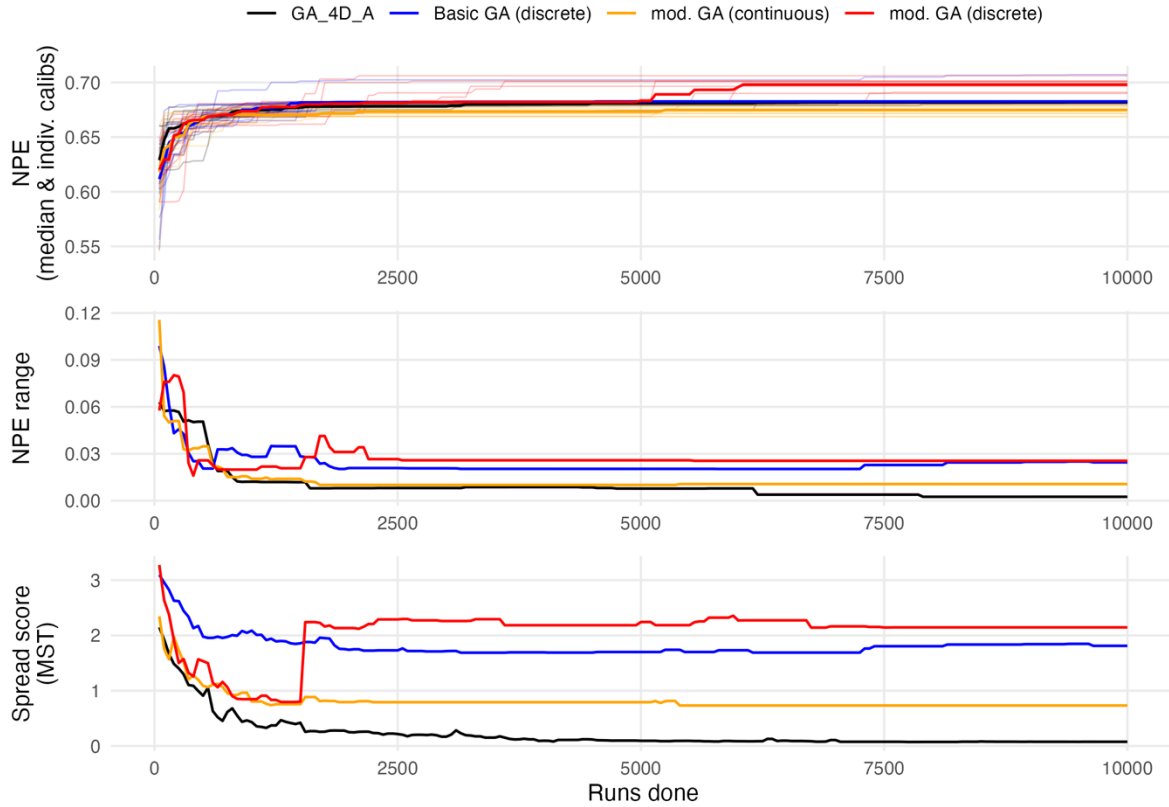


Figure 16: NPE, NPE range and spread score of 10 calibration outputs of basic and modified versions of the GA for the 4D-volume 2426_4D_A corresponding to Figures 9 and 15. The black line represents the original basic continuous version of the GA; the blue line represents the new discrete version of the basic GA; and orange and red lines represent the modified GA. For this 4D-volume, the discrete version of the modified GA (red lines) is the only version detecting the cluster of the global optimum.

This discrete version of the modified GA reaches the predefined goal of exploring different high-performance clusters one after the other. Nevertheless, this discrete version generally reaches lower NPE values when compared to the basic GA in parameter spaces with a single optimum. By contrast, the **continuous version of the modified GA** always displays unsatisfactory results.

For all 4D-volumes, the new **discrete version of the basic GA** overall displays the best results. When using NPE values as the main metric, outputs are sometimes significantly higher, and always at least as good as the ones of the basic GA (continuous version). The NPE ranges of this discrete GA version are often maintained small, hinting at a precise hit. The spread scores are generally higher for the modified GA, as expected by design. But this feature is not fully exploitable in 4D, as the parameter spaces contain a maximum of

two local optima. The spread score is a more interesting tool when calibrating in the full dimensionality, where many more optima could exist.

Summarized, in a 4D space, the new discrete version of the basic GA generally displays the best results. But the discrete version of the modified GA is the best at finding different high-performance clusters in some specific multimodal cases. For a more detailed insight, the results of all 12 4D-volumes are displayed in the [Appendix IV](#).

13D Analysis

In 13D, there is a noticeable contrast between the results of the Swiss catchments and the results of the European catchments. For the Swiss catchments, the new **discrete version of the basic GA** and the **discrete modified GA** display significantly higher NPE outputs, when compared to the basic continuous GA (e.g., catchment 2155 in [Figure 17](#)). This is not the case for the European catchments: here the **basic GA** (continuous and discrete versions) displays the best results (e.g., catchment DEBB0132 in [Figure 18](#)). Generally, the **continuous version of the modified GA** once again displays unsatisfactory results for all catchments, with lower NPE values reached.

The results show that the spread score is larger for the modified GA, as expected by design. Nevertheless, because of the large differences in NPE outputs, this feature remains secondary to define which version of the GA is more valuable: Interesting parameter sets are primarily chosen for high NPE values.

For a more detailed insight, the results for all 14 catchments are displayed in the [Appendix IV](#) and [Table 8](#) shows a summary of the abilities of the different versions of the GA.

Table 8: Summary of the abilities of the different versions of the GA in 4D and 13D. See [Table 7](#) for a precise description of the different GA versions.

GA version	4D	13D	
	Swiss catchments	Swiss catch.	European catch.
Basic GA (continuous)	Limited (see First Part)	Limited	Good
Basic GA (new discrete version)	<u>Overall best</u>	<u>Overall best</u>	<u>Overall best</u>
Mod. GA (continuous)	unsatisfactory	unsatisfactory	unsatisfactory
Mod. GA (discrete)	Best in specific cases	Good	Limited

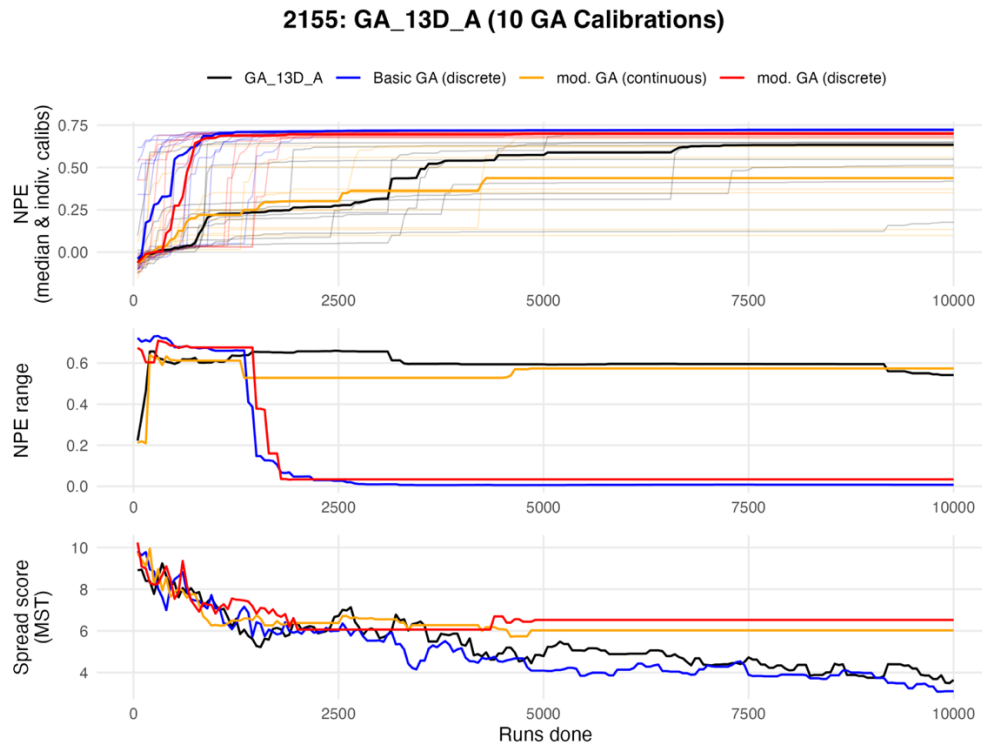


Figure 17: NPE, NPE range and spread score of 10 calibration outputs of basic and modified versions of the GA for the catchment 2155. The black line represents the original basic continuous version of the GA; the blue line represents the new discrete version of the basic GA; and orange and red lines represent the modified GA. For this catchment, the discrete GA versions display the best results.

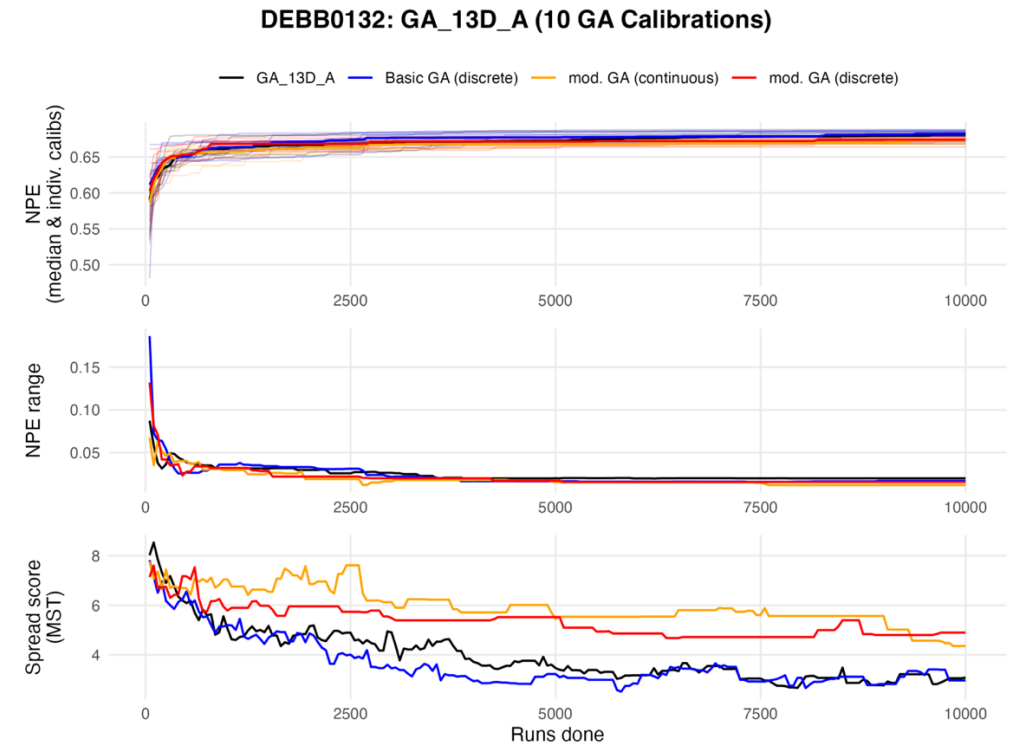


Figure 18: NPE, NPE range and spread score of 10 calibration outputs of basic and modified versions of the GA for the catchment DEBB0132. The black line represents the original basic continuous version of the GA; the blue line represents the new discrete version of the basic GA; and orange and red lines represent the modified GA. For this catchment, the modified versions of the GA do not display better results.

Discussion

Tradeoff Between Exploration and Efficiency

The restart routine of the modified GA should show the common tradeoff between exploration and efficiency, as presented by [Fukunaga \(1998\)](#). When restarting the GA too early, it does not have time to efficiently search within a newly detected region and does not reach the best values of the cluster. If restarted too late, the GA stagnates in the same region without a possibility to reach new zones. Interestingly, the **continuous version of the modified GA** displays weak abilities in both features.

Efficiency of the Continuous Version of the Modified Genetic Algorithm

NPE values are systematically lower for the continuous version of the modified GA compared with the continuous version of the basic GA. This suggests that the restart routine happens too soon, hindering a deeper scan within a precise region. The restart could be triggered too early for some catchments, due to the relatively high value of the variable SpreadRatioMin (see [Tables 5, 6 and Figure 13](#)). In other words, the diversity of the GA population members is still relatively high and prone to recombine into better performing parameter sets when the restart is already being triggered. Future research could focus on this point and systematically test lower values of SpreadRatioMin to assess if GA outputs are then more valuable.

Nevertheless, the current settings of the modified GA generally limit a deeper search as too low values of SpreadRatioMin do not trigger a restart at all, as discussed previously (see [Figure 13](#)). This is because the internal spread score (MST) quickly stabilizes after a few generations, rather than constantly decreasing. Future research could test a new restart routine: Instead of restarting the GA immediately after the diversity collapses, the GA should continue searching for a predefined number of generations. Only after this delay, the GA should be restarted to explore new regions of the parameter space.

Interestingly, this issue related to a potential restart routine happening too soon does not happen for the discrete version of the modified GA. This point is discussed later.

Exploration of the Continuous Version of the Modified Genetic Algorithm

A restart triggered too early should encourage exploration and detect different high-performance zones, even if the local maximum within these zones is not reached. Unfortunately, this is not the case both in 4D and 13D, despite different local optima existing at least in 4D and very probably in 13D as well (see [First Part](#)). Results showed that this is not due to a too limited space removal in the modified GA design. An explanation for this failure is that after a zone is being excluded, the probability of finding another high-performance cluster (i.e., another local optimum) remains very low. Indeed, because other clusters are very narrow, the GA wanders around the first zone without finding better NPE outputs. In other words, the efficiency of the GA is sacrificed without the exploration capacity to be increased due to probabilistic issues. This behavior confirms the evidence found in the [First Part](#) of this thesis: The GA aims at the largest high-performance cluster rather than aiming at the overall best cluster.

Edge Position of the Parameter K2

The **discrete version of the basic GA** shows the best abilities overall. The higher NPE values found by this version are constantly linked to output positions of the parameter K2 situated at the edge of the searched range. Specifically, when restarting the GA or during mutation, the probability of randomly selecting this edge position is much larger in a discrete case. This appears to be a valuable advantage, as the NPE values are extremely sensitive around the lower edge of K2 for all Swiss catchments. This is presented in [Figure 19](#). Similar behavior in other parameters could not be observed in the results.

If in 4D the **discrete version of the modified GA** presents a significant advantage in some specific scenarios (e.g., 4D-volume 2426_4D_A in [Figures 15 and 16](#)), this is not the case in 13D. In full dimensionality, the good performances of the discrete GAs for the Swiss catchments are only due to the sensitive behavior of K2 around its lower edge value. In other words, the good performances are not due to the restart routine removing space. Indeed, this is confirmed by the positions of the K2 outputs not being different for both versions (i.e., the modified GA does not reach a different local optimum compared with the basic GA version). This behavior is presented in [Figure 19](#) for catchment 2155.

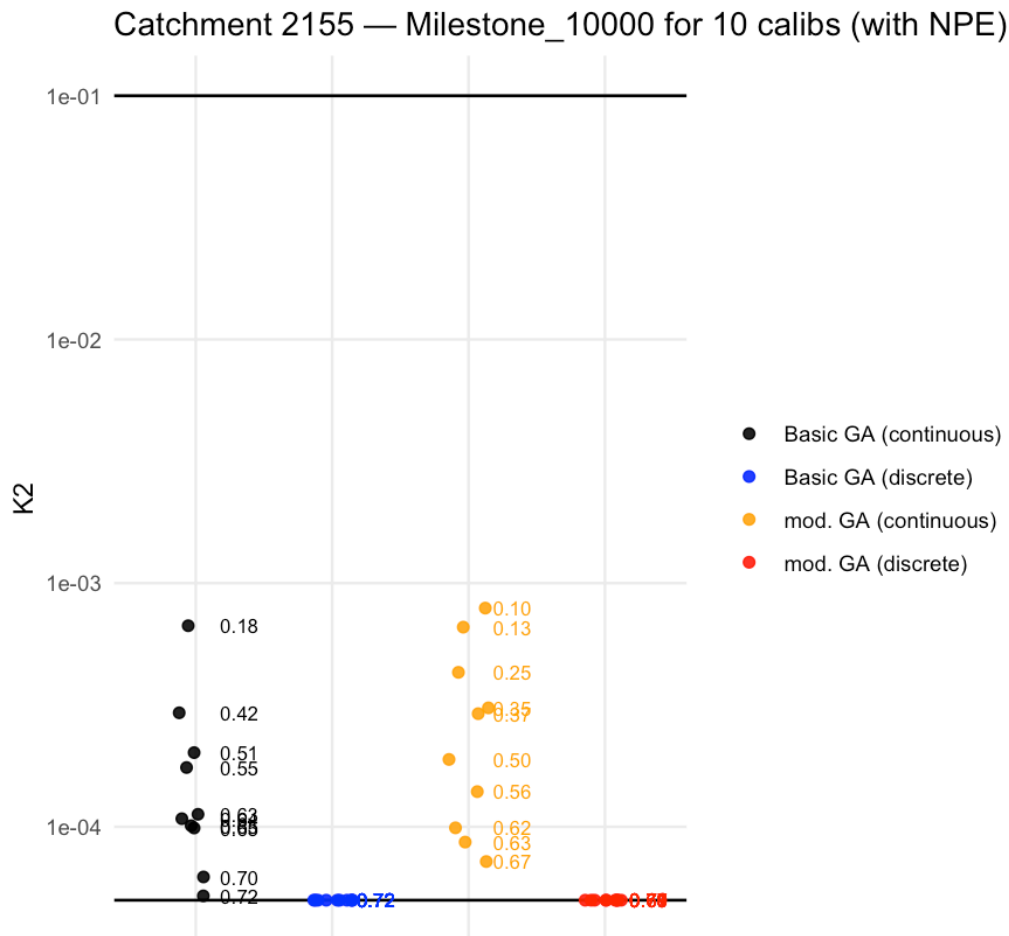


Figure 19: Output positions (with corresponding NPE value) of the parameter $K2$ for 10 full dimension (13D) calibrations with different versions of the GA (catchment 2155). NPE values quickly decrease for higher values of $K2$, hinting at a very sensitive behavior around the lower edge value of this parameter. This behavior benefits the discrete versions of the GA.

Undiscovered Local Optima in 13D

For the European catchments, because of a reduced to nonexistent sensitivity of the parameter $K2$ around its lower edge value, the advantage of a discrete GA version is weakened. This explains similar NPE output values when comparing the discrete and continuous versions of the basic GA. Interestingly, for the Swiss catchments all the optimal values of $K2$ are situated at the lower edge of its range. These values are not reachable during the calibration of the European catchments, due to their different $K2$ range (see [Table 1](#)). A calibration process for the extended $K2$ range (i.e., to match the range of the Swiss catchments) also does not detect a new global optimum. Nevertheless, this new global optimum does exist in some cases (i.e., for catchments DEBB0132 and DEBB0136) but remains undiscovered during calibration. This is confirmed by a calibration process executed only in the lower $K2$ range and displaying higher NPE output values, as presented in

Figure 20 for the catchment DEBB0132. Unfortunately, the modified GA with restart routine and space removal also fails to detect this high-performance cluster.

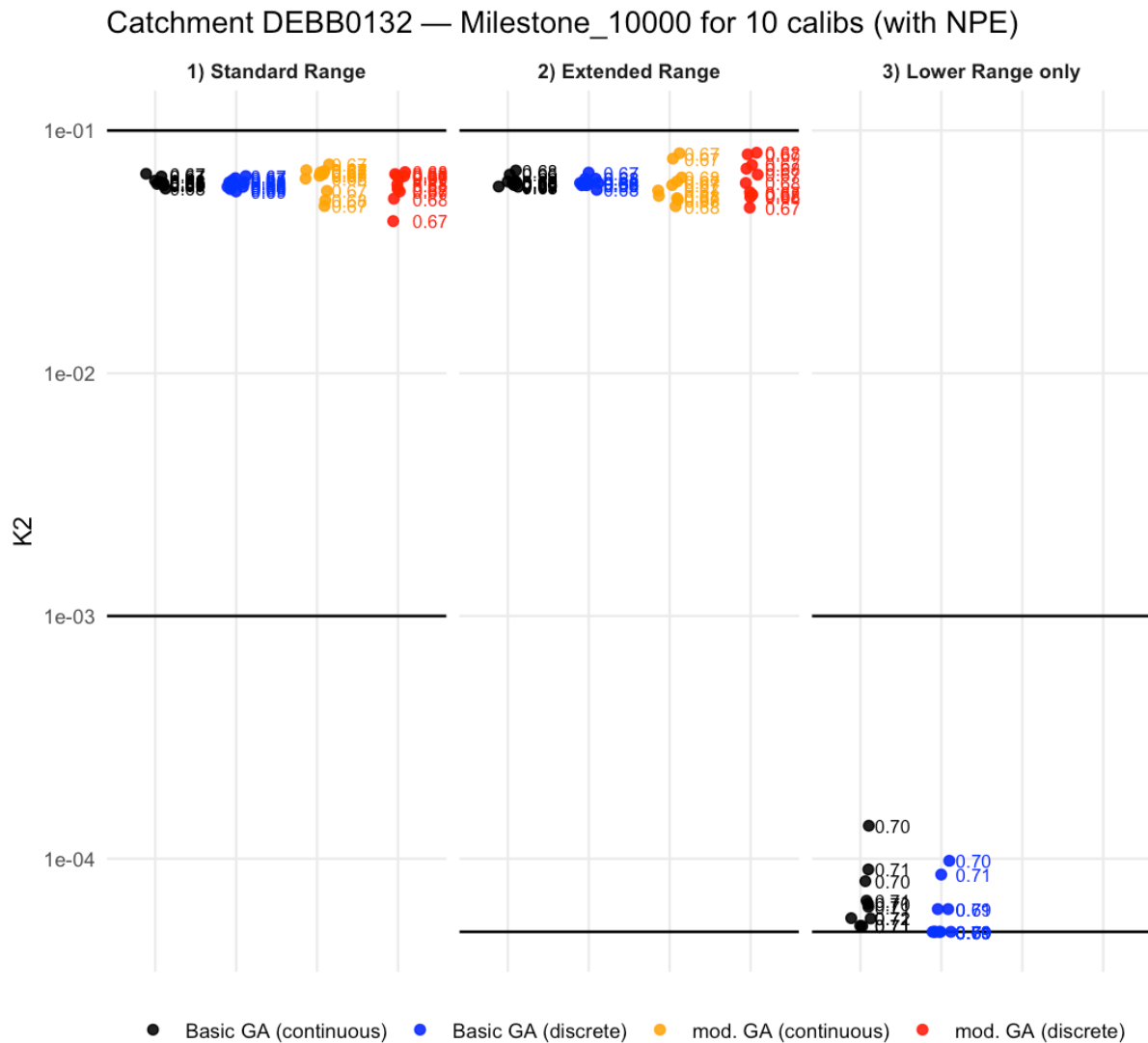


Figure 20: Output positions (with corresponding NPE value) of the parameter $K2$ for 10 full dimension (13D) calibrations with different versions of the GA and different $K2$ ranges (catchment DEBB0132). Black lines indicate the $K2$ range of each GA calibration. The global optimum (NPE value of about 0.70) found when calibrating only in the lower $K2$ range remains undiscovered when calibrating in the extended range.

The same explanation applies here: The GA cannot probabilistically find this second local optimum due to its low volume. If in 4D the modification and the discrete characteristics of the GA allow to probabilistically reach new high-performance zones, this is not the case in a much larger 13D parameter space. Nevertheless, this gives a novel indication about the 13D *landscape structure*: Most parameter spaces seem to display one vast high-performance cluster, easily detectable by a basic GA. Some catchments display a second (and often better performing) high-performance cluster large enough to be detected by a

restart routine or a discrete design in special cases. And the next potential high-performance clusters, if they exist, seem very narrow and remain undetected. Detecting them will likely remain a probabilistic challenge, independently on GA improvements. Nevertheless, searching the parameter space separately for successive ranges of a given parameter produced valuable exploratory results in this thesis. This approach could therefore be explored further in future research.

K2 as the Most Influential Parameter in High-Performance Regions

The results suggests that the NPE range of GA calibration outputs is mainly defined by the behavior of the parameter K2 (i.e., if this parameter creates different identifiable local optima). Indeed, the behavior of this parameter consistently explains the results of the selection process conducted in the **First Part** to choose catchments based on their KGE range (**Table 2**). One essential question remains: Do other (probably very narrow) undiscovered alternative high-performance clusters linked to other parameters exist? The findings of this thesis, consistently highlighting K2 rather than other parameters despite the relatively large number of parameter spaces analyzed, suggests that this is not the case. But this possibility cannot be excluded, and future research could focus on this question, concentrating on different parameters or parameter combinations. By doing so, further problematic parameters could potentially appear, helping to locate other narrow optima.

Usage of a Modified or Discrete Genetic Algorithm

Using a modified GA in 13D seems a bit hazardous with outputs being directly linked to the *landscape structure* of the parameter space. A trustful GA should present stable characteristics and be efficient regardless of the given *structure*. Specifically, it should not sacrifice efficiency for a potentially failed exploration. For this reason, we do not recommend using the modified versions of the GA in the full dimensionality. But this is different in a reduced space: The new discrete version of the modified GA seems to present an interesting potential linked to more favorable probabilities in detecting secondary clusters.

Nevertheless, a more precise analysis should be done for more catchments. If K2 (or another parameter) does not create different alternative stable systems with different high-performance clusters, the qualities of the new GAs are useless. Also, choosing which

parameters to keep and calibrate in a reduced space is complex. Indeed, the analysis showed the central role of K2 in influencing NPE outputs. But the Sobol analysis presented in the [First Part](#) only found this parameter to show a limited influence on the output variance. This could seem contradictory, but this observation can be explained as follows: Some parameters become very sensitive in very narrow sub-regions of the parameter space. Specifically, K2 is highly sensitive in high-performance regions resulting from a specific combination of precise values in other parameters. On the other hand, a general Sobol analysis over the full parameter space does not show this behavior as it tests for output variance also in areas that might react completely differently. In other words, the output variance effect of very narrow regions is overpowered when combined with other much larger and possibly less reactive regions. In addition, some parameters that are not very sensitive in these narrow sub-regions are very sensitive in larger low-NPE regions, presenting the opposite effect. This behavior shows the limit of using a Sobol analysis to select influential parameters for the HBV model, particularly when only very narrow regions of interest are finally being used.

Finally, using the discrete version of the basic GA demonstrated strong abilities in finding high-performing parameter sets. Future research is required to confirm this behavior on more catchments, with a potential wider use. Nevertheless, one strong limitation needs to be acknowledged and tested: when using the discrete version of the basic GA, the diversity of the K2 outputs of different calibrations is strongly reduced to one (edge) value in most cases. The efficiency of ensemble forecast is mainly based on slight differences between parameter sets and single parameter values ([Liechti and Zappa, 2016](#)). Therefore, there is a risk for ensemble predictions to lose their core value, with an underestimation of discharge uncertainty despite higher-performing parameter sets. It should be tested whether the discrete version of the basic GA adds value to everyday predictions, or if it is mainly a strong theoretical computational solution with limited practical use.

Conclusion

This thesis shows that understanding the interaction between GAs and *landscape structures* is essential to ensure that calibration outputs reflect the true range of plausible model behaviors. In this sense, the thesis gives new insights into the *structure* of the HBV parameter space and the search mechanism of the GA related to this *structure*.

First, we proved that not *all* optima can be detected with the current structure of a GA: GAs aim at the largest high-performance cluster rather than aiming at the overall best cluster. Also, the successive detection of multiple optima during the same calibration process remains unlikely in many cases, due to population diversity loss and probability biases. These findings have direct and practical implications for hydrology. Currently, the calibration results obtained in HBV do not only reflect the behavior of the catchment, but also the limits of the optimization algorithm. In many cases, the selected parameter sets do not fully represent the true range of possible system behaviors. As a result, runoff simulations and uncertainty estimates are affected. In this sense, part of the model's apparent limitations actually come from the calibration process. Improving the exploration of the parameter space, or at least acknowledging the limitations of the current method, is essential for a more reliable interpretation of HBV results.

Second, the thesis indicates that for HBV-light, besides further modifying and optimizing the GA, another strategy could improve the search in the parameter space: carefully selecting and reducing the allowed range of K2 (and other parameters if future research is done) based on the geographical properties of the catchment. Doing so reduces the complexity of the *landscape structure* and makes different high-performance clusters easier to detect, as the overall parameter space becomes smaller. However, it is not always possible to adjust parameter ranges individually when calibrating multiple catchments. Therefore, future research could also focus on defining a new calibration routine that divides the range of K2 into several individual calibrations. This separate multiple-range calibration process could potentially detect new high-performance clusters before recombining the NPE outputs together at a later step.

Third, the newly created modified GA, based on a restart routine and removing search space, showed interesting results in reduced dimensionality. It could therefore be

potentially used to optimize the parameter space search of other (hydrological) models with high compensation mechanisms and containing less parameters. Future research could be conducted in this direction, e.g., for models such as the *Génie Rural à 4 paramètres Journalier (GR4J)* ([Perrin et al., 2003](#)). For such a model, the capacity of the modified GA to jump from one high-performance cluster to another seems highly valuable. Calibrating such a model only once to detect the different high-performance clusters, rather than repeating the process multiple times to always land in the same region, significantly reduces computational costs.

Finally, and more broadly, the results of this thesis suggest that the limitations observed are not specific to HBV but are inherent to GAs searching complex and multimodal *landscapes*. This implies that calibration processes in many environmental models may systematically fail to detect relevant solutions. Model calibration is not a purely technical step: It defines how the system behavior is interpreted. The choice of optimization algorithm directly influences which modeled realities are considered plausible, and which ones remain undiscovered.

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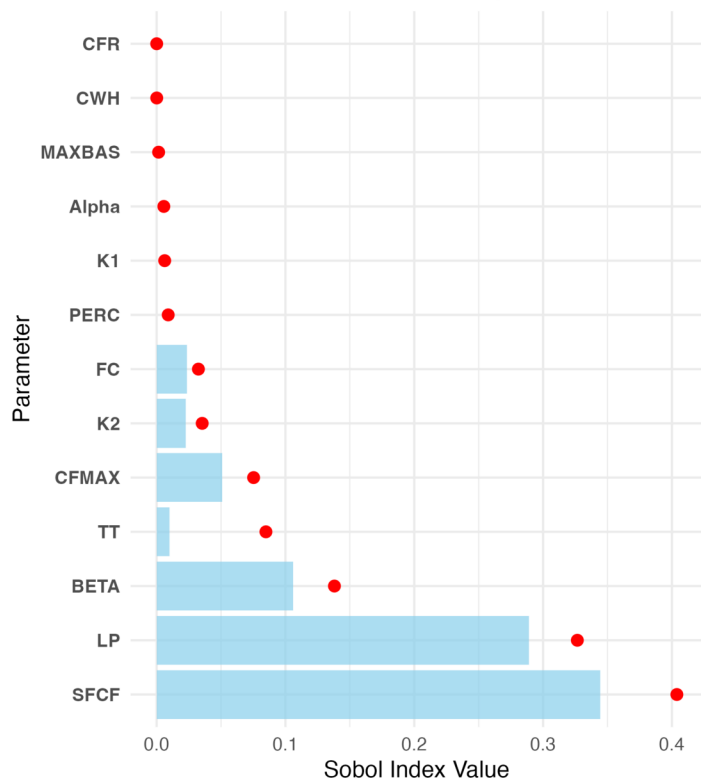
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Appendix

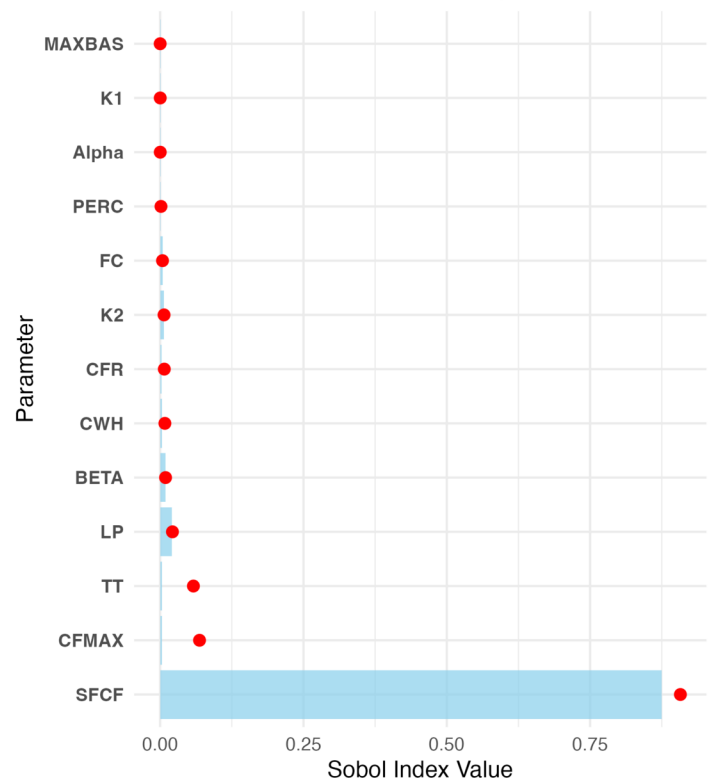
The Appendix contains the following:

- I. Sobol Analyses (pp. 57-60)
- II. 3D projections of the 4D-volumes (including GA calibration paths), combined with the persistence diagram of the TDA and the corresponding NPE values (pp. 61-144)
- III. Coverage plots of the 4D-volumes with the position of the GA members at different milestones (pp. 145-168)
- IV. Analyses of the modified GA (in 4D and 13D) combining following metrics: 1) NPE (median of 10 GA calibrations); 2) NPE range among 10 GA calibrations; and 3) spread score (MST of the outputs of 10 GA calibrations) (pp. 169-181)

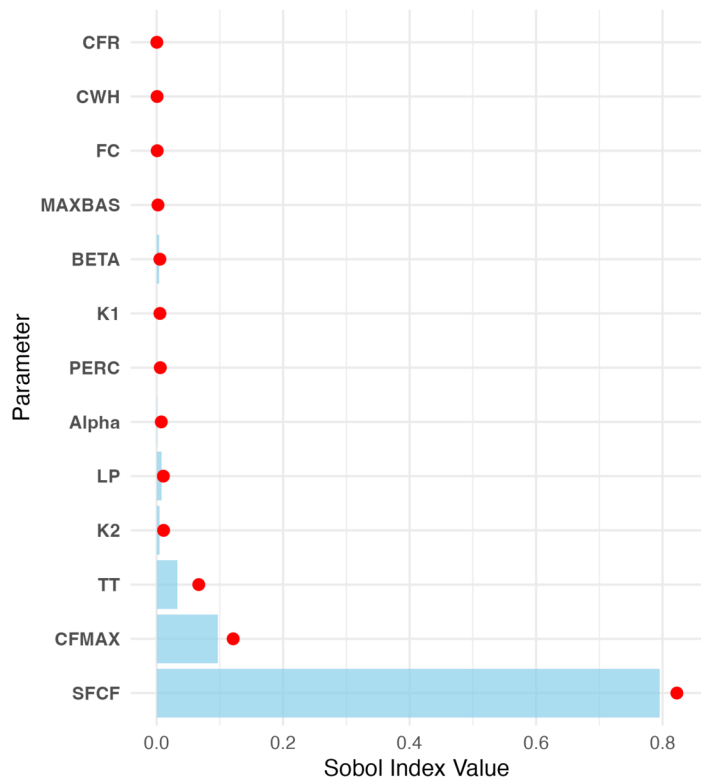
2155, Sobol Sensitivity Indices



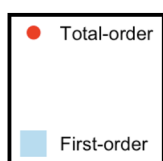
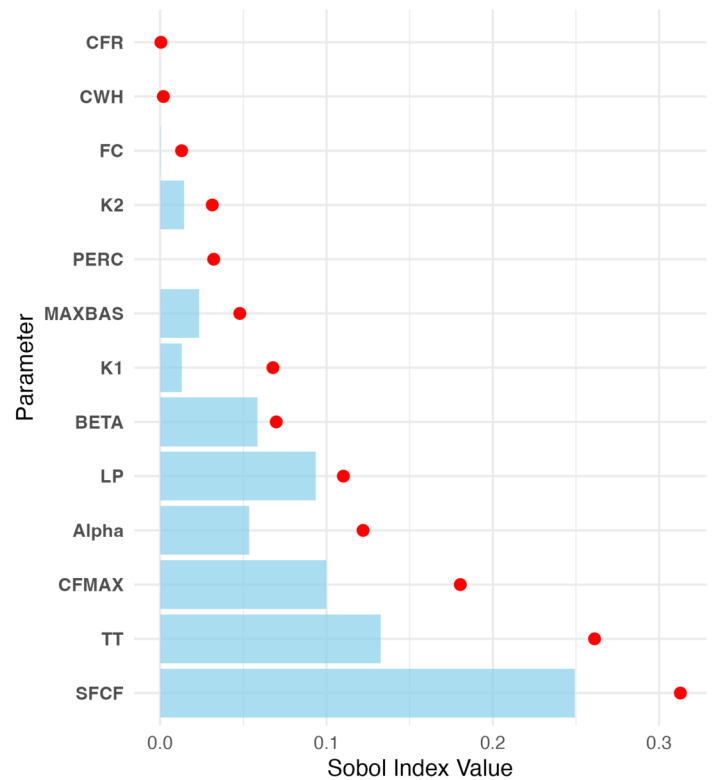
2403, Sobol Sensitivity Indices



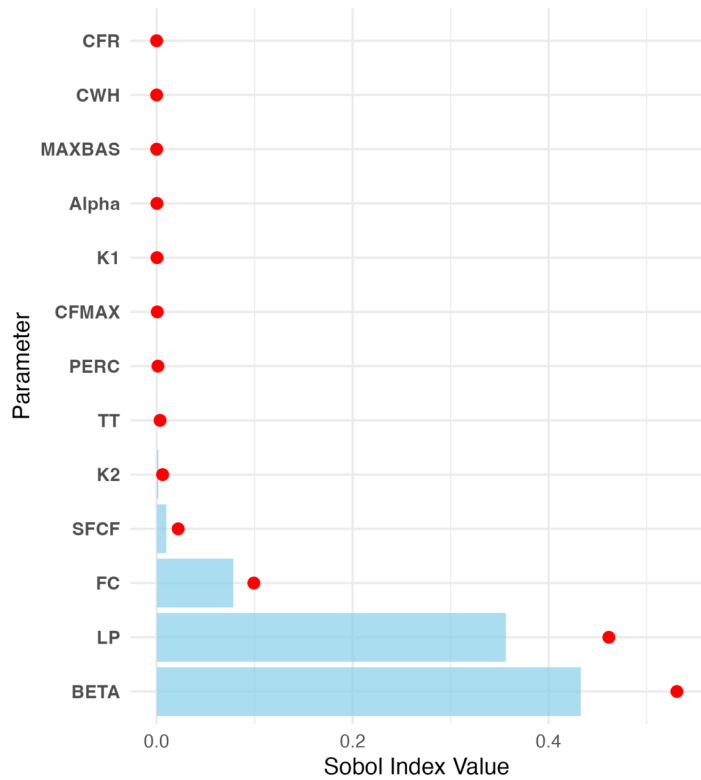
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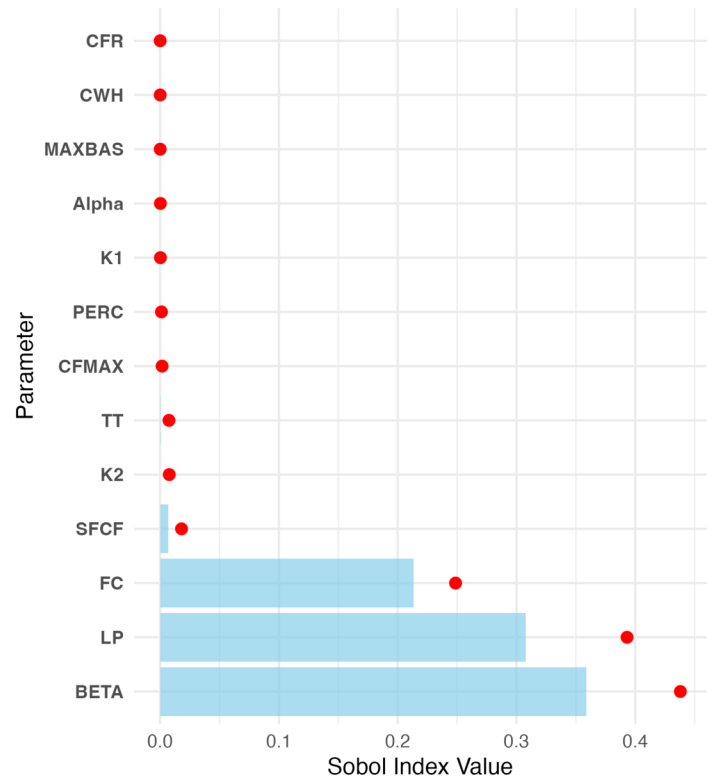
5014, Sobol Sensitivity Indices



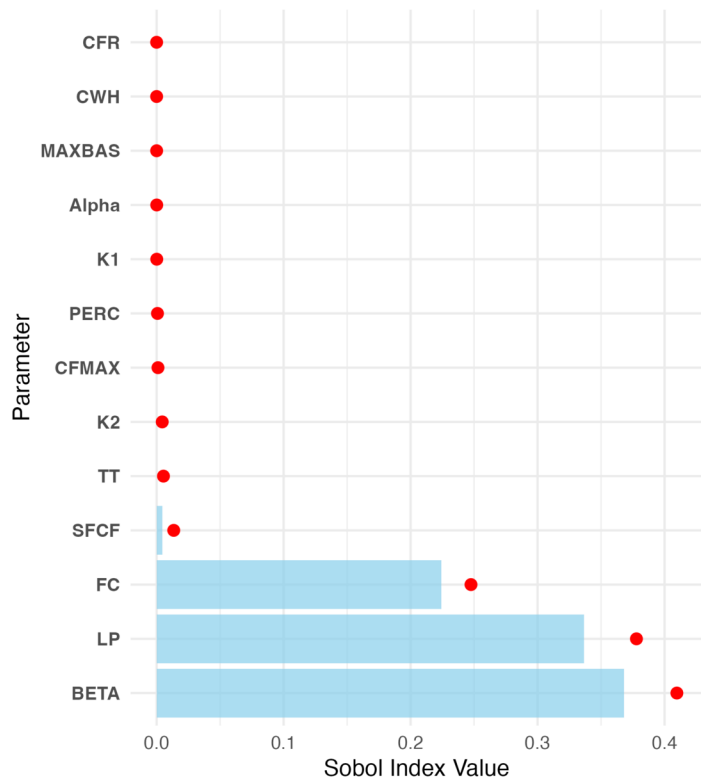
CZ000098, Sobol Sensitivity Indices



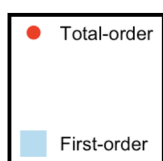
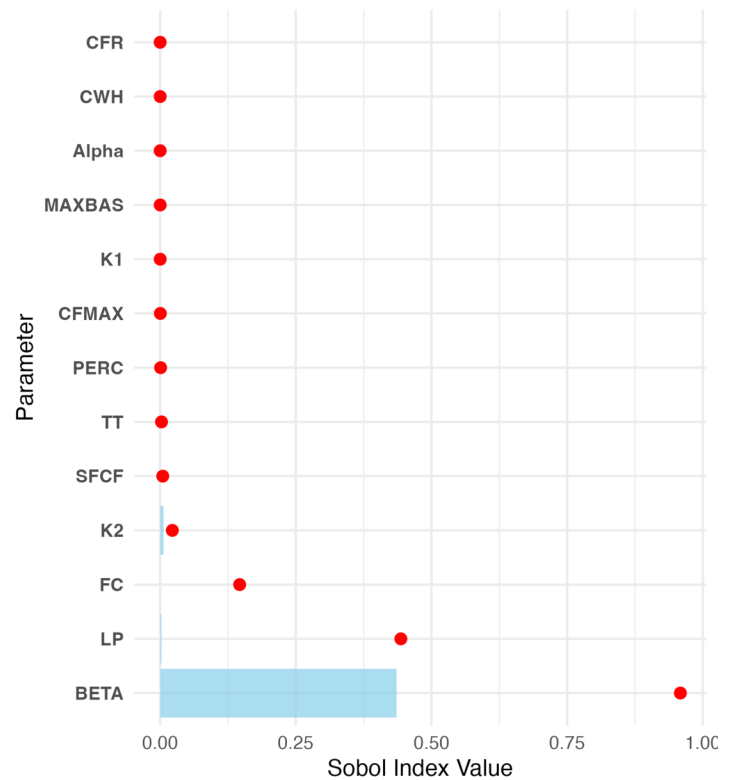
DEBB0132, Sobol Sensitivity Indices



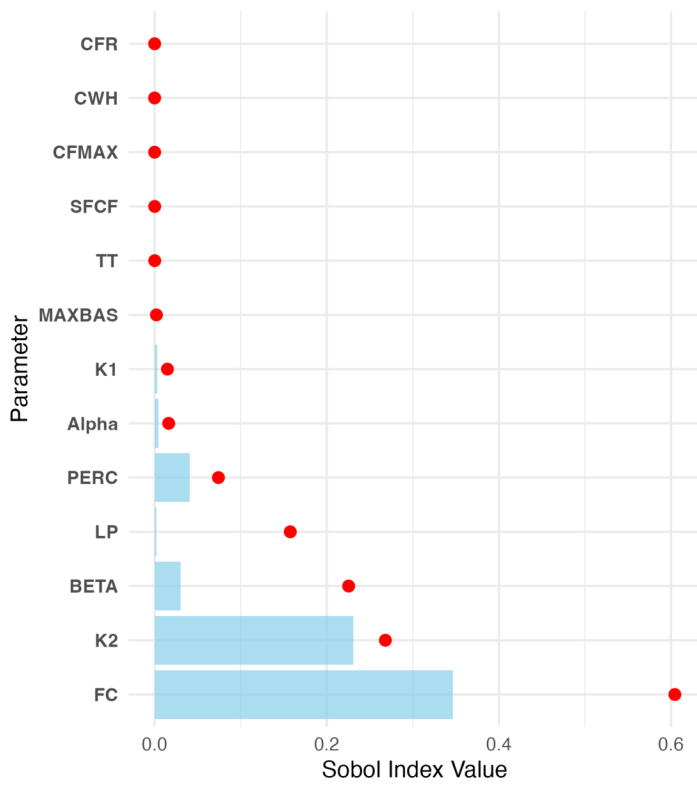
DEBB0136, Sobol Sensitivity Indices



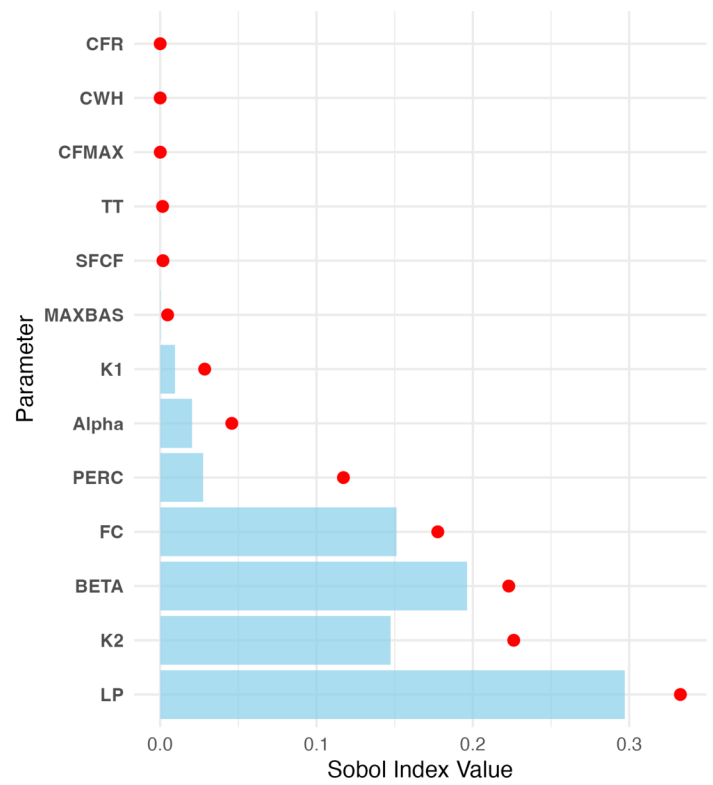
ES000356, Sobol Sensitivity Indices



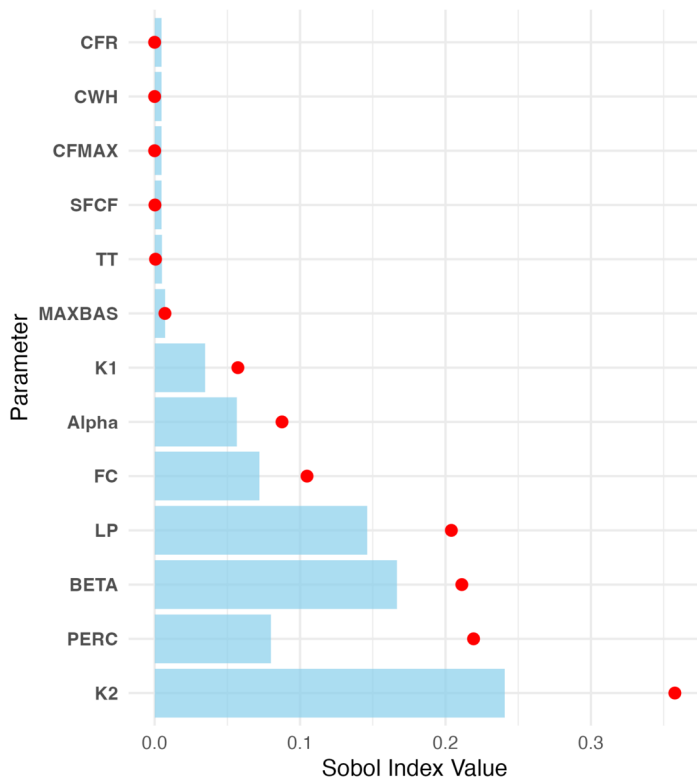
ES001323, Sobol Sensitivity Indices



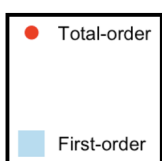
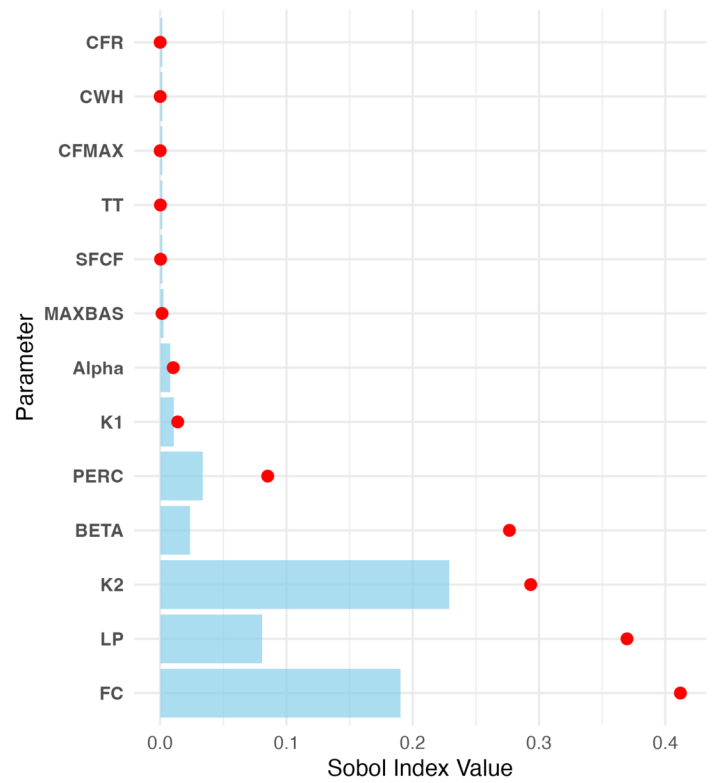
FR000672, Sobol Sensitivity Indices



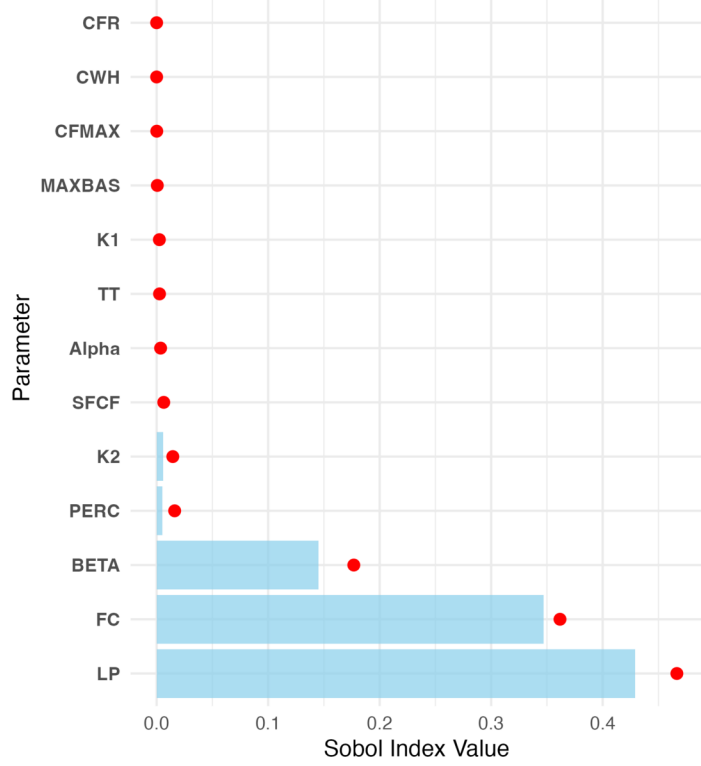
FR000730, Sobol Sensitivity Indices



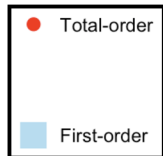
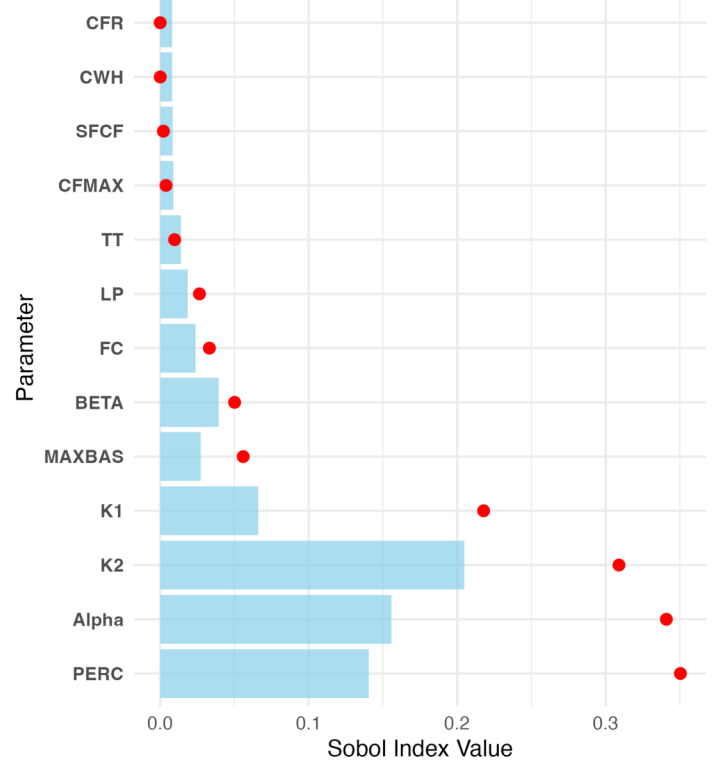
FR001413, Sobol Sensitivity Indices



GB000296, Sobol Sensitivity Indices

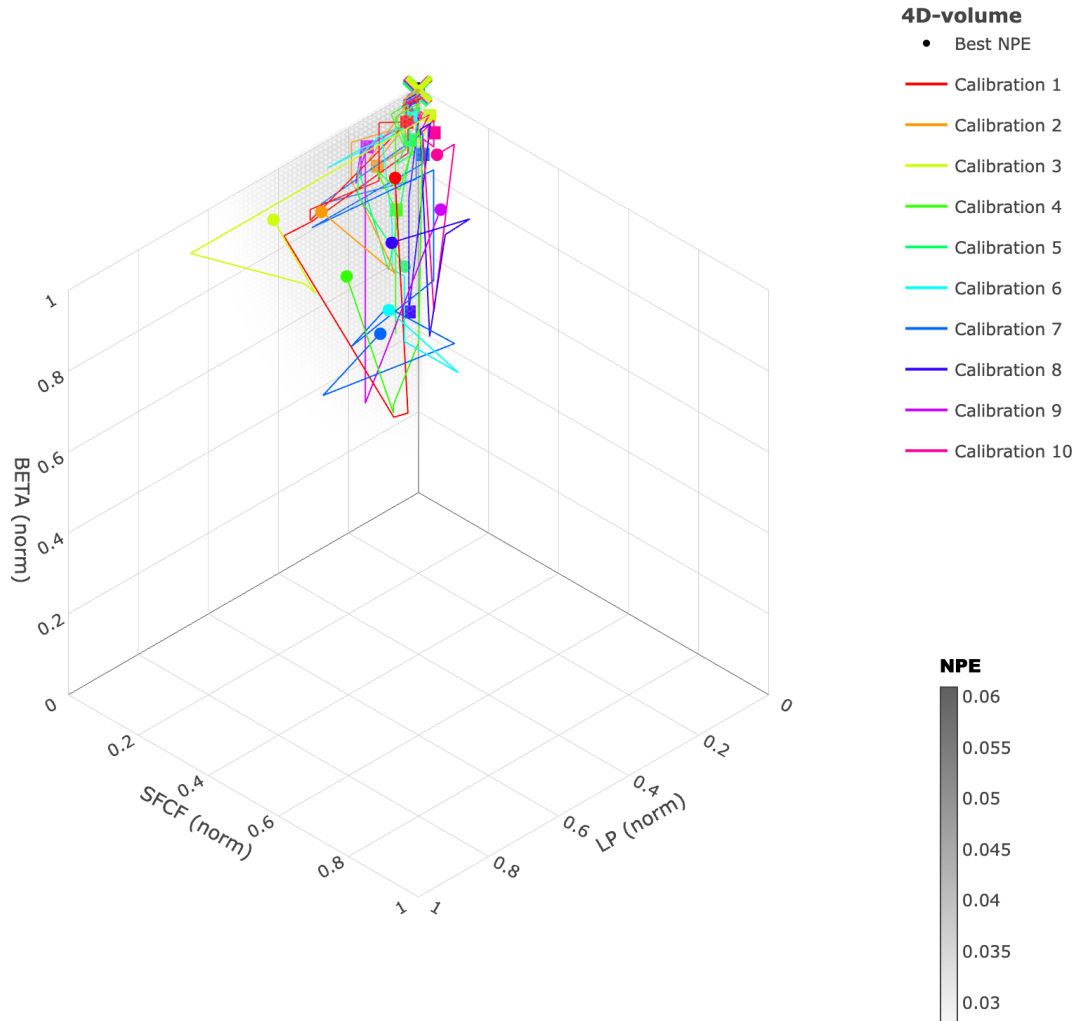


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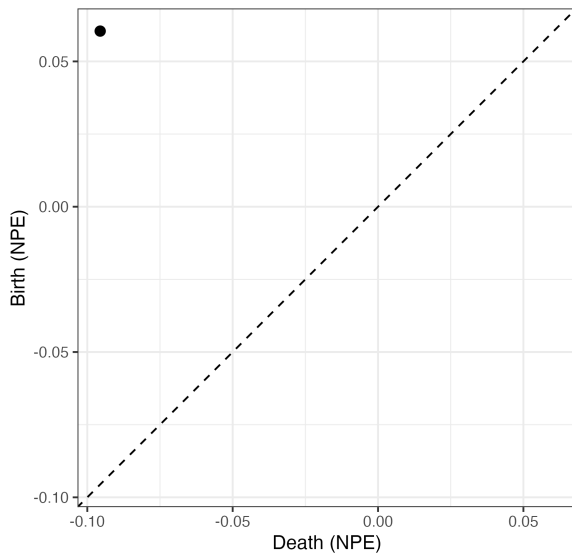


2155_4D_A, SFCF_LP_BETA_TT

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



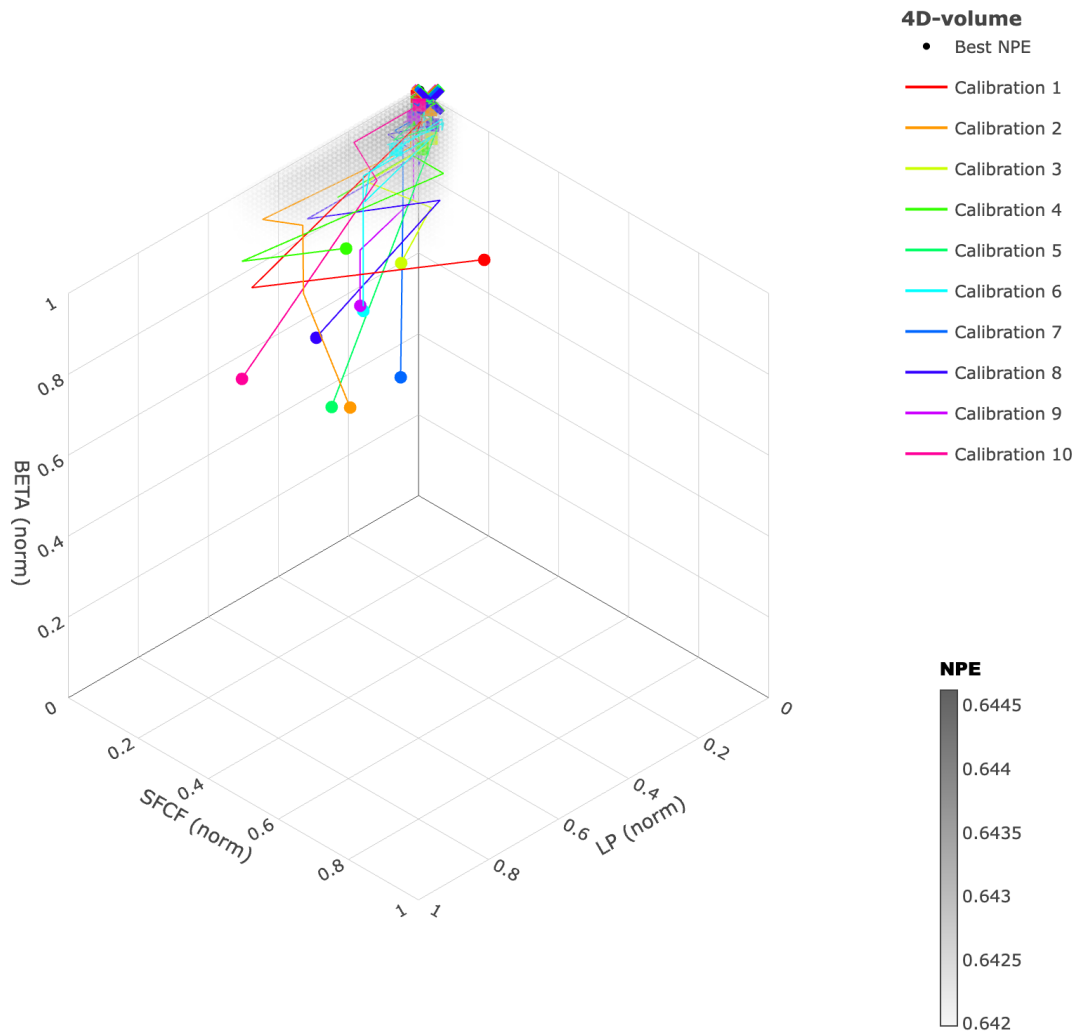
2155_4D_A: Persistence Diagram, top 5%



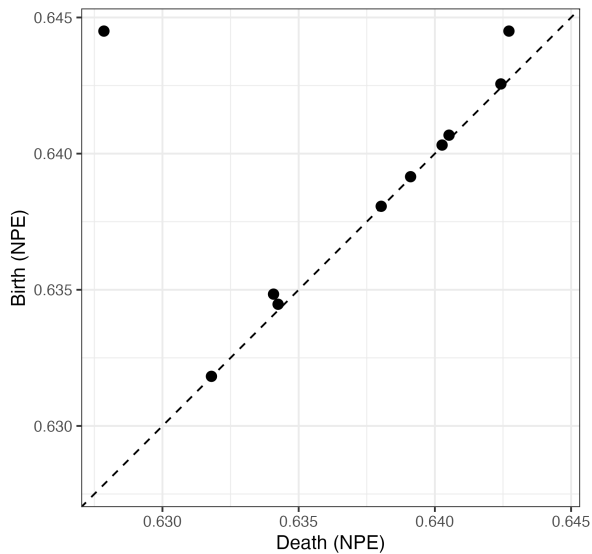
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.04884929	0.05720865	0.06016433	0.06022995	0.06091473
2	0.05417086	0.05708753	0.05818592	0.06035457	0.06091473
3	0.04014036	0.05879834	0.05879834	0.05879834	0.06091473
4	0.03070223	0.05627267	0.05975183	0.05984623	0.06091473
5	0.04683424	0.05590472	0.05640157	0.05994048	0.06091473
6	0.04849006	0.05913561	0.05945575	0.05967727	0.06091473
7	0.04668094	0.05950633	0.0604458	0.0605451	0.06091473
8	0.04340131	0.05747765	0.05854958	0.06046946	0.06091473
9	0.051003	0.05773303	0.05953778	0.06008673	0.06091473
10	0.03109316	0.05700477	0.05987655	0.0606506	0.06091473

2155_4D_B, SFCF_LP_BETA_TT

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



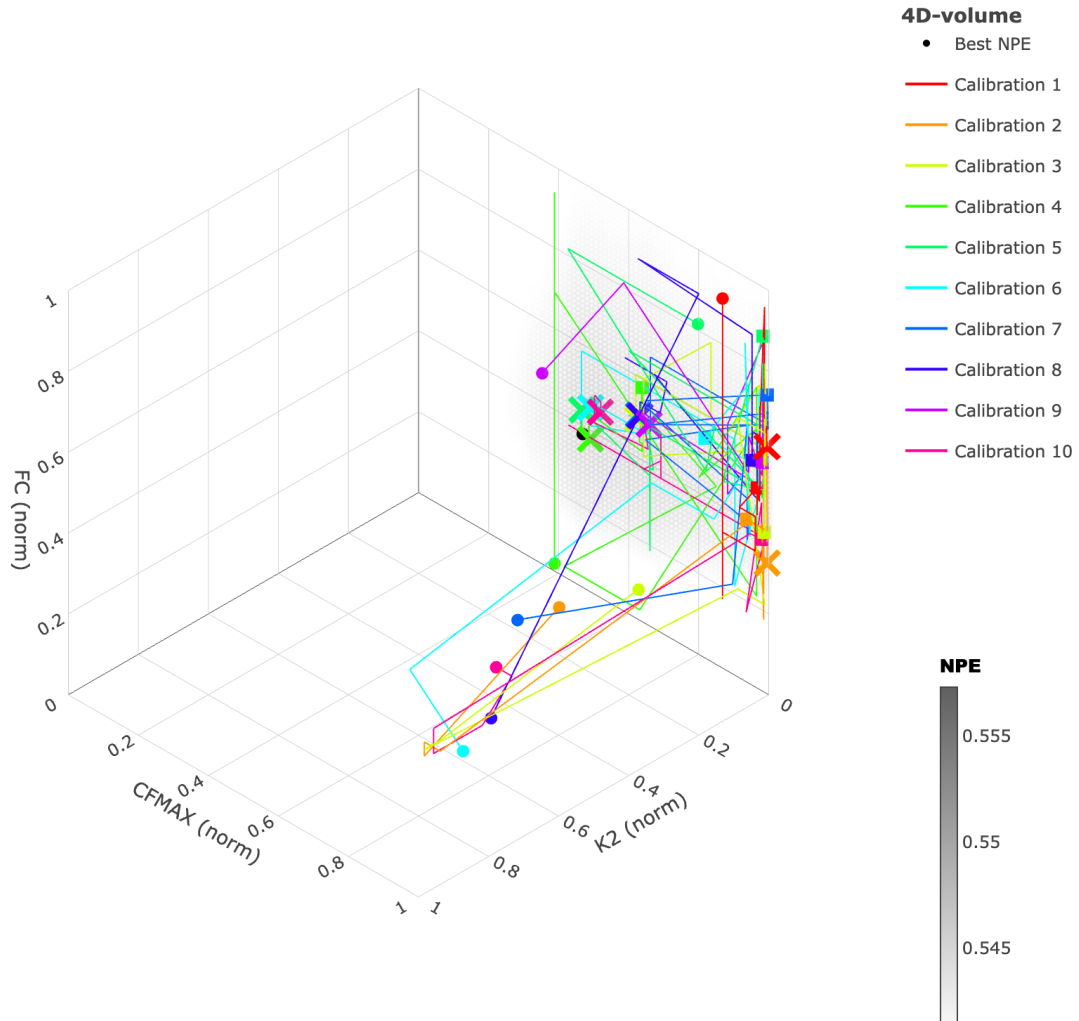
2155_4D_B: Persistence Diagram, top 5%



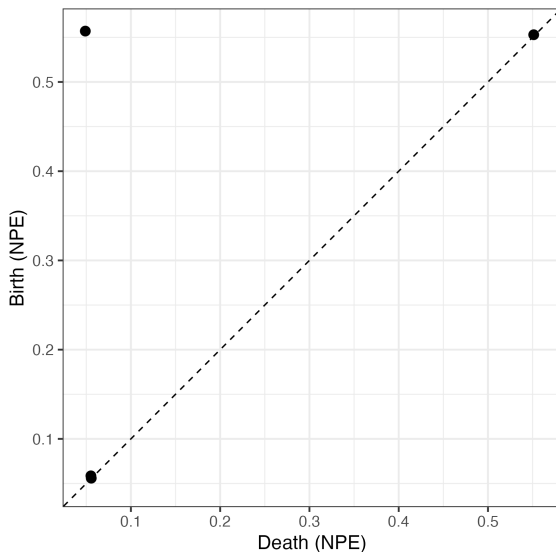
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.6444028	0.64488268	0.64492667	0.644967	0.64461903
2	0.6441174	0.64455793	0.64491502	0.64491594	0.64461903
3	0.64409604	0.64453882	0.64459367	0.64493803	0.64461903
4	0.6437841	0.64459664	0.64466827	0.64478499	0.64461903
5	0.64438101	0.64459069	0.64465024	0.64491142	0.64461903
6	0.6437346	0.64475085	0.64487604	0.64494562	0.64461903
7	0.64319366	0.64455257	0.64468356	0.64472378	0.64461903
8	0.64439896	0.64459129	0.6446397	0.64465778	0.64461903
9	0.64405263	0.64428509	0.64480053	0.64489541	0.64461903
10	0.64408216	0.64467119	0.6447626	0.64493734	0.64461903

2155_4D_D, CFMAX_K2_FC_PERC

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



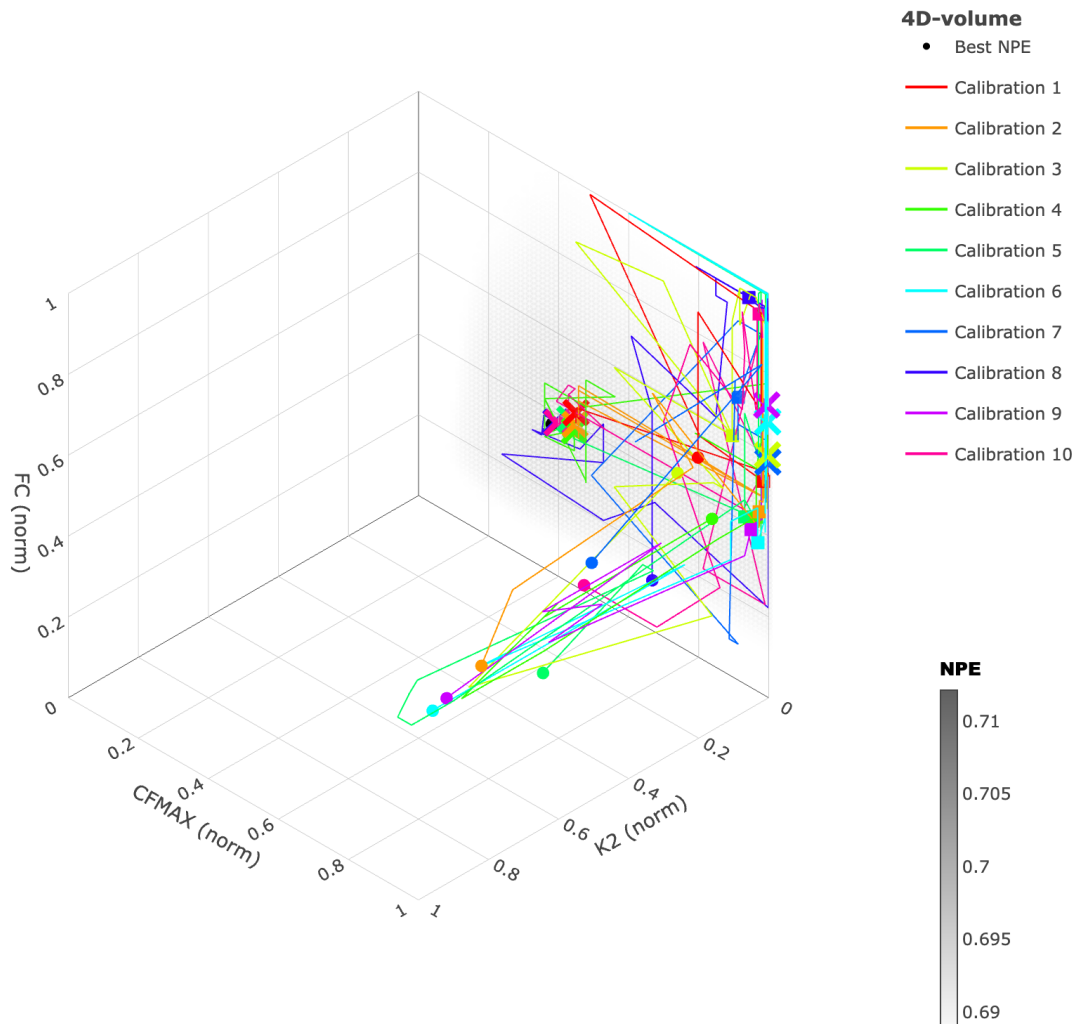
2155_4D_D: Persistence Diagram, top 5%



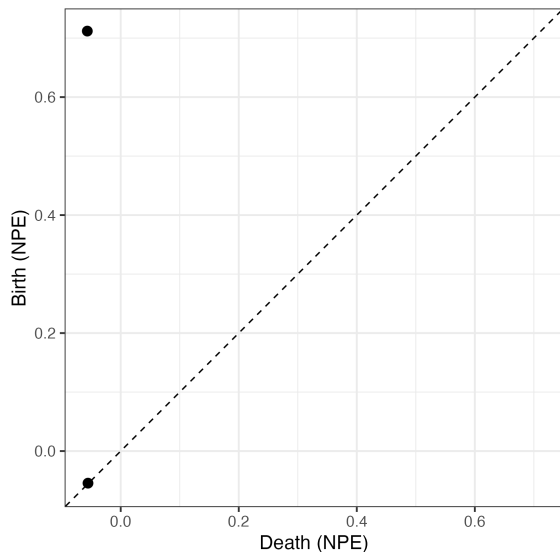
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.1317698	0.15408057	0.22710685	0.2822842	0.55729745
2	0.07628152	0.0775949	0.29133153	0.41403837	0.55729745
3	0.11941215	0.22951133	0.22959011	0.47202146	0.55729745
4	0.54950438	0.55283362	0.55295334	0.55318832	0.55729745
5	0.2658122	0.26722825	0.41680578	0.54375215	0.55729745
6	0.35553954	0.35658355	0.49639845	0.52508289	0.55729745
7	0.38422477	0.38506648	0.45029971	0.45036395	0.55729745
8	0.20552334	0.43999107	0.4405635	0.44075255	0.55729745
9	0.16947152	0.18610096	0.4209972	0.4228636	0.55729745
10	0.10976356	0.49990163	0.50055536	0.50065605	0.55729745

2155_4D_E, CFMAX_K2_FC_PERC

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



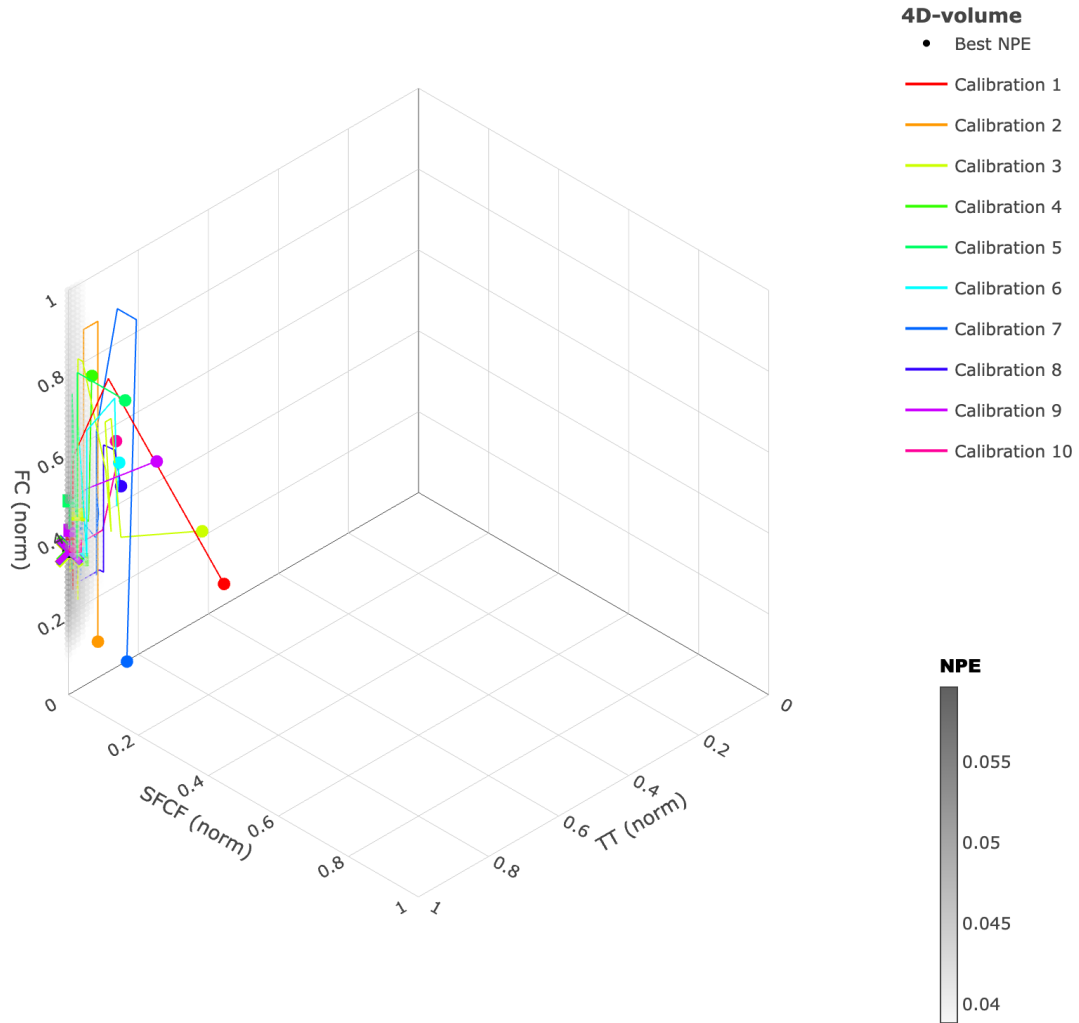
2155_4D_E: Persistence Diagram, top 5%



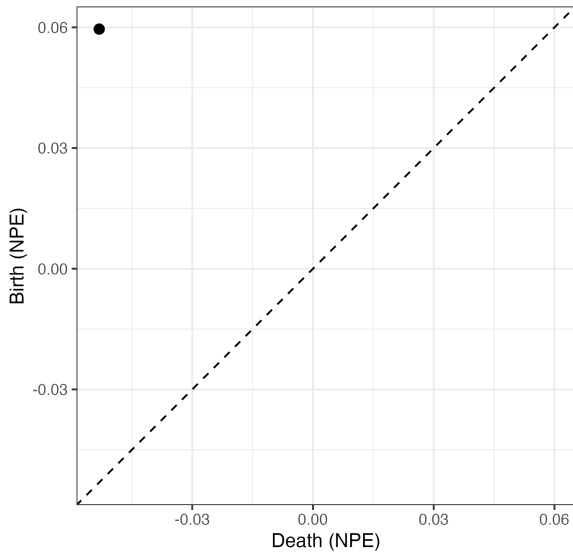
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.6405252	0.64081697	0.64112111	0.6412991	0.71212501
2	-0.02781555	0.63377112	0.64108841	0.64153646	0.71212501
3	0.15733275	0.16451426	0.48257086	0.57121818	0.71212501
4	-0.04890936	0.17691928	0.17700429	0.6641034	0.71212501
5	-0.00602492	0.64901209	0.64914646	0.6491564	0.71212501
6	-0.04785777	0.06248392	0.18351465	0.51191897	0.71212501
7	0.56134166	0.56266541	0.56266541	0.60030592	0.71212501
8	0.30375185	0.67707484	0.70804489	0.70836408	0.71212501
9	-0.0489032	0.44898924	0.54957251	0.5495734	0.71212501
10	0.08844215	0.6672179	0.66886345	0.66901262	0.71212501

2155_4D_J, SFCF_TT_FC_Alpha

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



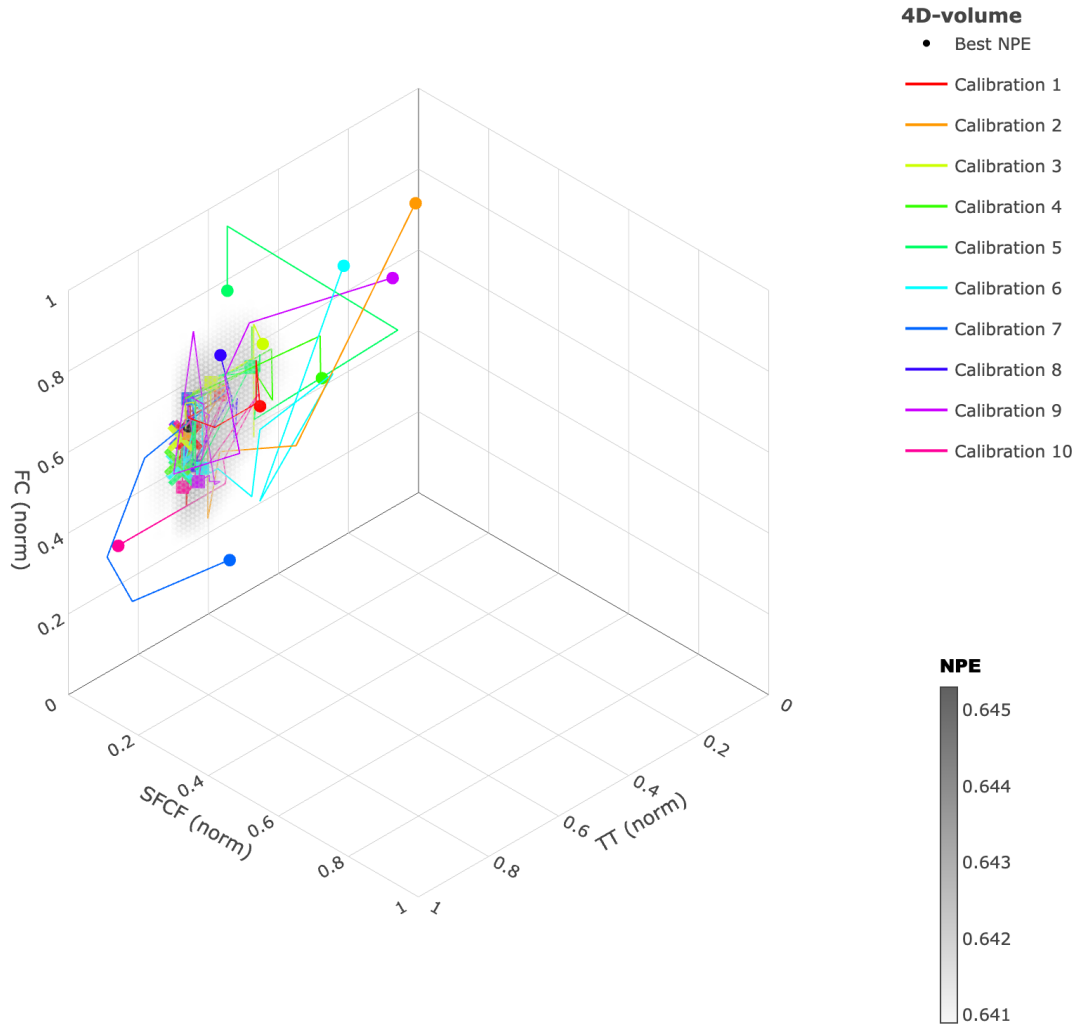
2155_4D_J: Persistence Diagram, top 5%



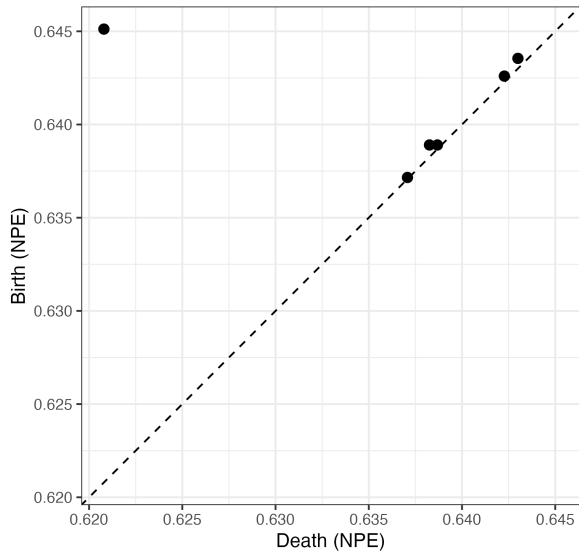
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.05749962	0.05929895	0.05930313	0.05934018	0.05961949
2	0.05451705	0.05773834	0.05775464	0.05926606	0.05961949
3	0.04172937	0.05730462	0.05731874	0.0576022	0.05961949
4	0.05101316	0.0557801	0.05776646	0.05780428	0.05961949
5	0.0578106	0.05901778	0.05912054	0.05912136	0.05961949
6	0.04963689	0.0582012	0.05821117	0.05825482	0.05961949
7	0.05440205	0.0579102	0.0579102	0.05871025	0.05961949
8	0.05386244	0.05822479	0.05828814	0.05831398	0.05961949
9	0.0572167	0.05770985	0.05771262	0.05771925	0.05961949
10	0.05272441	0.05663756	0.05919048	0.05919376	0.05961949

2155_4D_K, SFCF_TT_FC_Alpha

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



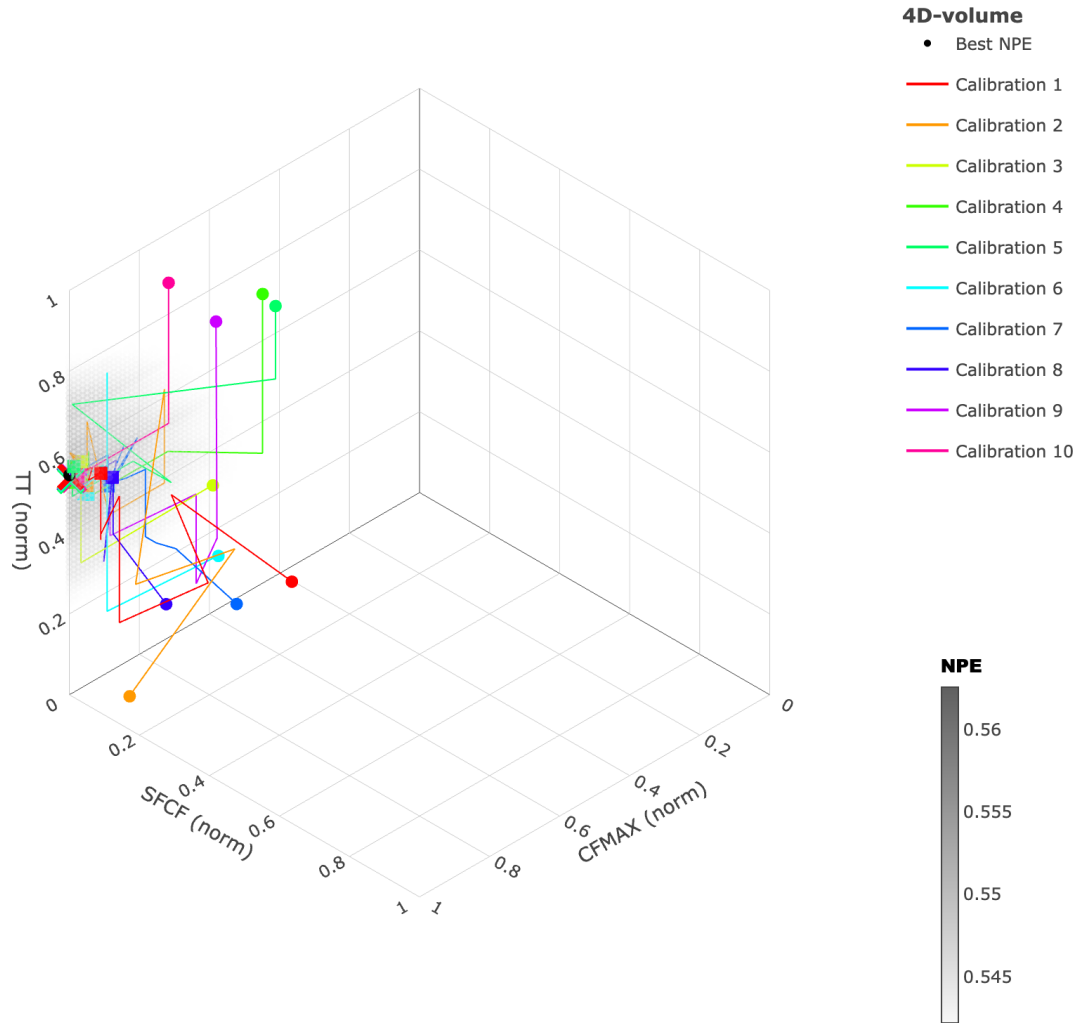
2155_4D_K: Persistence Diagram, top 5%



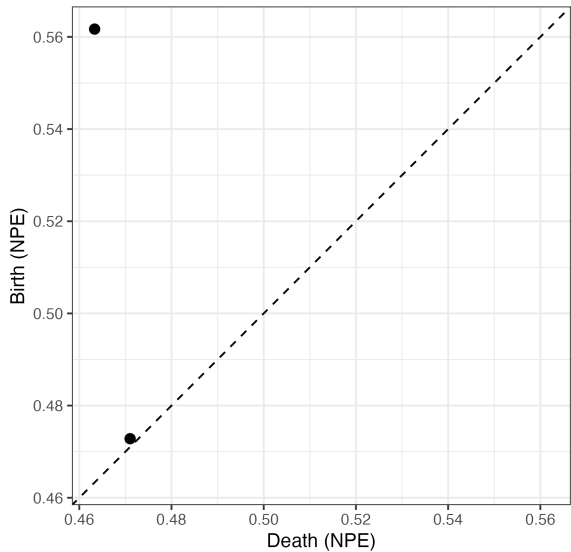
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.6433801	0.64515586	0.64545827	0.64548244	0.64529932
2	0.6452381	0.64529852	0.64529852	0.64544509	0.64529932
3	0.64406104	0.64491722	0.64524601	0.64551682	0.64529932
4	0.64302916	0.64502426	0.6454788	0.64551735	0.64529932
5	0.64355981	0.64482103	0.64527921	0.64549736	0.64529932
6	0.64347267	0.64507344	0.64542291	0.64556717	0.64529932
7	0.64438374	0.64531356	0.64532511	0.64549906	0.64529932
8	0.64374949	0.64504576	0.64546508	0.64552748	0.64529932
9	0.64365808	0.64523484	0.64535995	0.6454819	0.64529932
10	0.64429191	0.64532703	0.64536718	0.64549975	0.64529932

2403_4D_A, SFCF_CFMAX_TT_LP

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



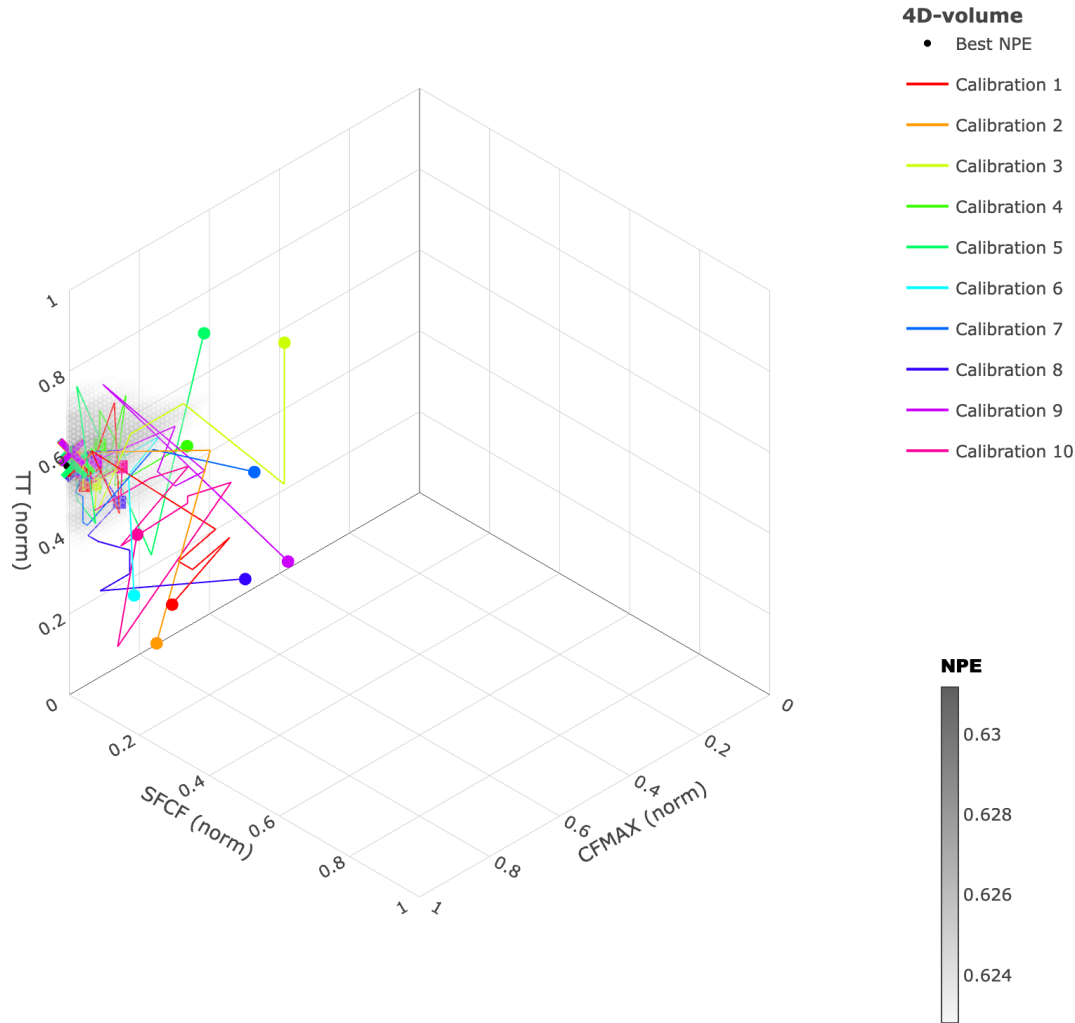
2403_4D_A: Persistence Diagram, top 5%



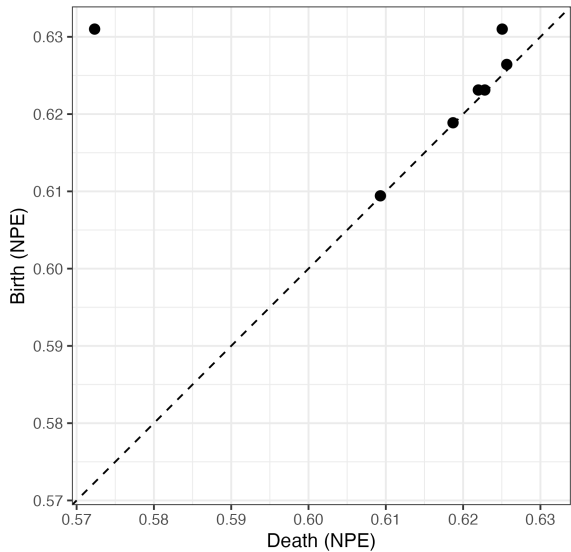
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.54560093	0.55719408	0.56219363	0.56221588	0.56254647
2	0.5573864	0.56138983	0.56154704	0.56239653	0.56254647
3	0.55819868	0.56075422	0.56191342	0.56212605	0.56254647
4	0.56001761	0.56143858	0.56203394	0.56215338	0.56254647
5	0.55796863	0.5592569	0.55959723	0.56111637	0.56254647
6	0.55700553	0.56100689	0.56203415	0.56206908	0.56254647
7	0.55591724	0.56208239	0.56208239	0.56208239	0.56254647
8	0.5471744	0.56087843	0.56225349	0.56225349	0.56254647
9	0.56003846	0.56236436	0.56238688	0.56264913	0.56254647
10	0.55822399	0.55948035	0.56035333	0.56042711	0.56254647

2403_4D_B, SFCF_CFMAX_TT_LP

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



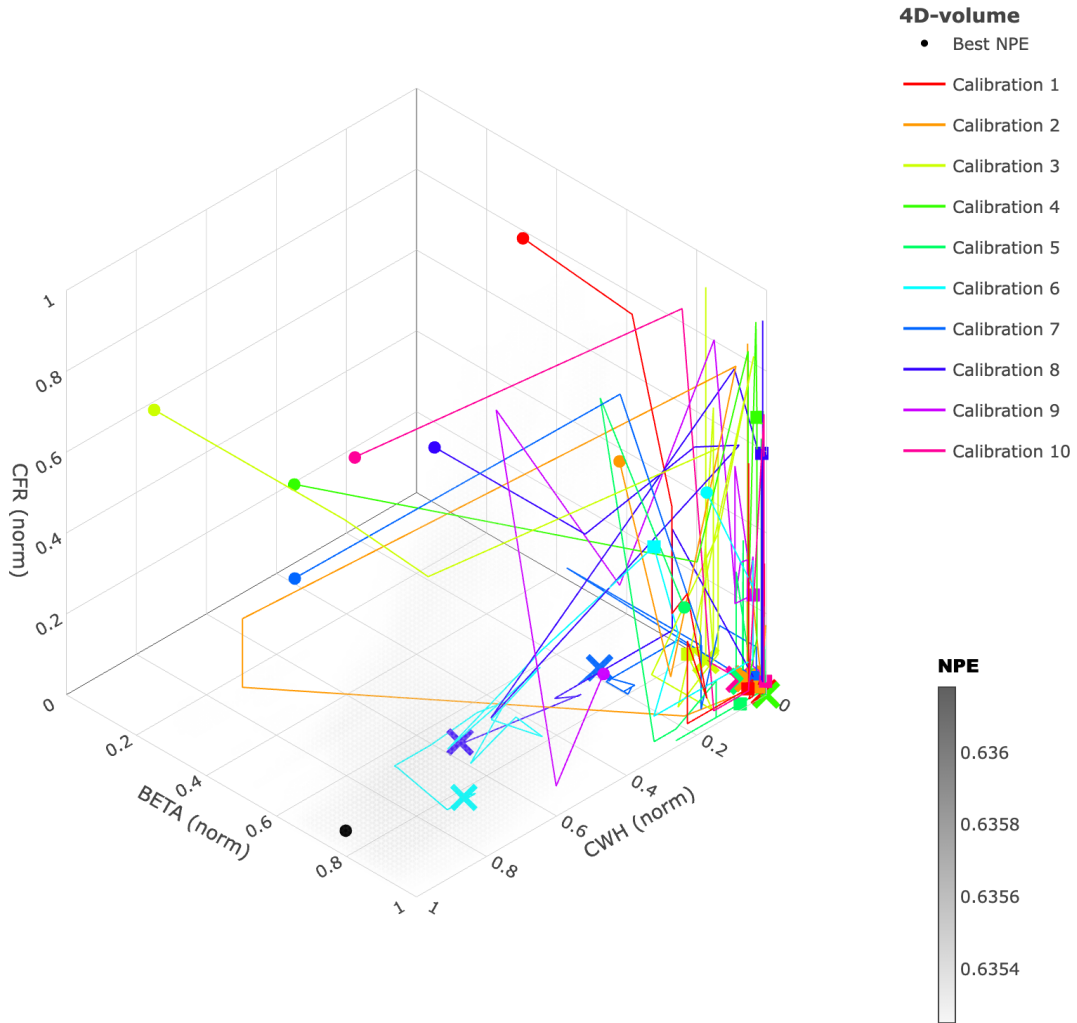
2403_4D_B: Persistence Diagram, top 5%



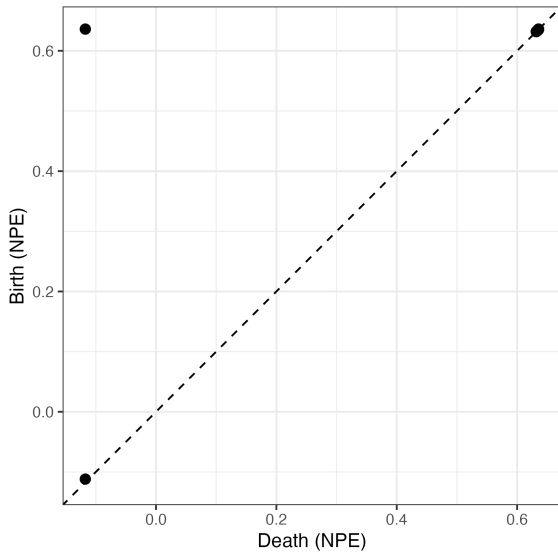
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.62774407	0.63015189	0.63070356	0.63117055	0.63117353
2	0.63048346	0.63115921	0.63131741	0.63132689	0.63117353
3	0.62595794	0.63088432	0.63110146	0.63115593	0.63117353
4	0.62896098	0.63086961	0.63116254	0.6311884	0.63117353
5	0.63086973	0.63109887	0.63111179	0.6311607	0.63117353
6	0.63000448	0.63105469	0.63105469	0.63118182	0.63117353
7	0.63058876	0.63098479	0.63130382	0.63137484	0.63117353
8	0.62465011	0.63104745	0.63104745	0.63105179	0.63117353
9	0.62879043	0.63073068	0.63090108	0.63117555	0.63117353
10	0.62618856	0.63082451	0.6308862	0.63129962	0.63117353

2403_4D_D, BETA_CWH_CFR_K2

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



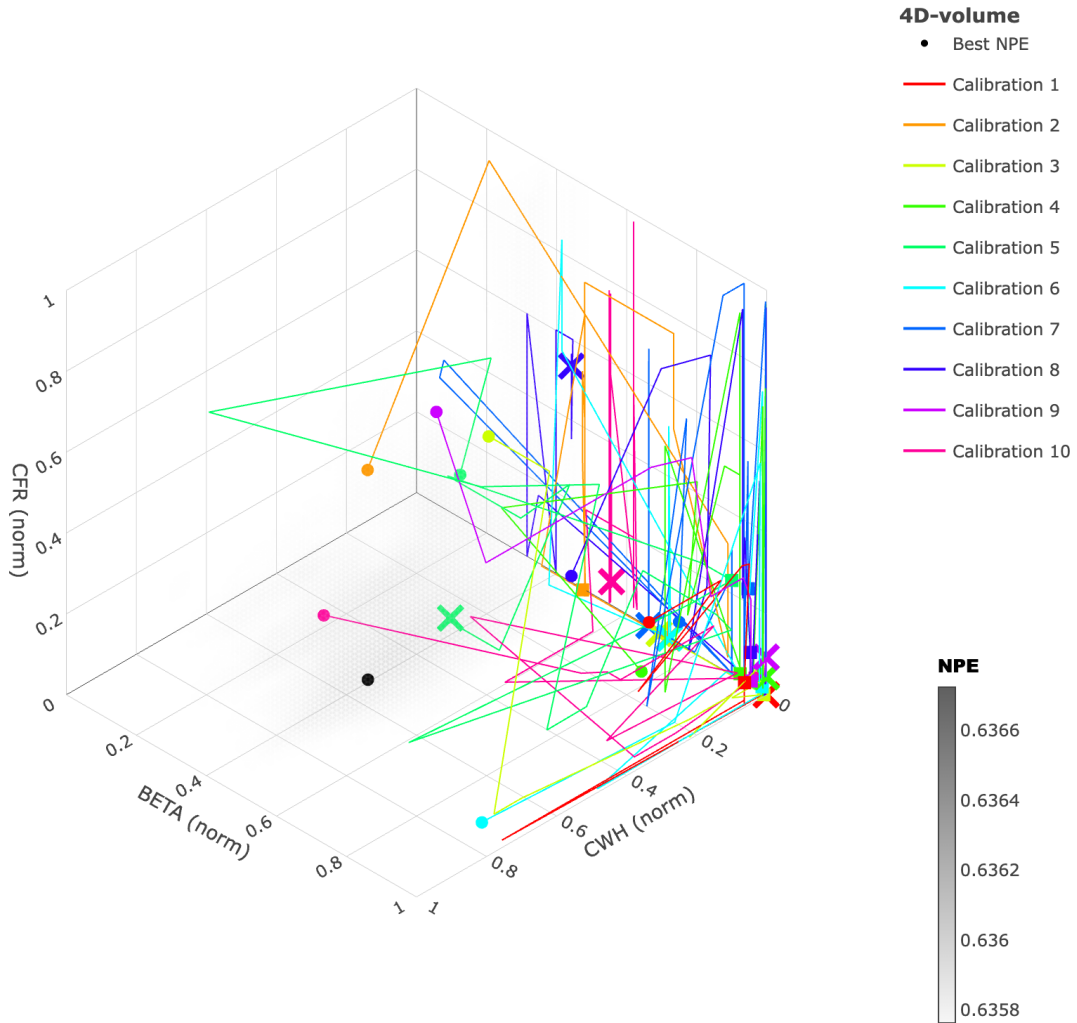
2403_4D_D: Persistence Diagram, top 5%



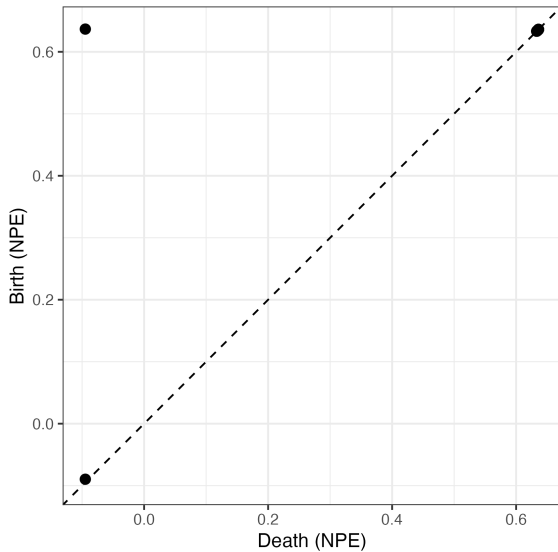
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.10944684	0.32356836	0.36018542	0.3602009	0.63618076
2	0.00139674	0.00152702	0.5642708	0.56428803	0.63618076
3	0.59244085	0.59259659	0.59265932	0.59265932	0.63618076
4	0.07074374	0.48772085	0.48779922	0.48781469	0.63618076
5	0.20557905	0.45975922	0.45975922	0.53758038	0.63618076
6	0.62972287	0.630895	0.63093838	0.63093838	0.63618076
7	0.5456313	0.61022784	0.61028887	0.61033093	0.63618076
8	0.11312521	0.11366358	0.61519149	0.6157585	0.63618076
9	-0.03645319	0.51487138	0.51487138	0.51487138	0.63618076
10	0.25857616	0.25859965	0.25860125	0.52685388	0.63618076

2403_4D_E, BETA_CWH_CFR_K2

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



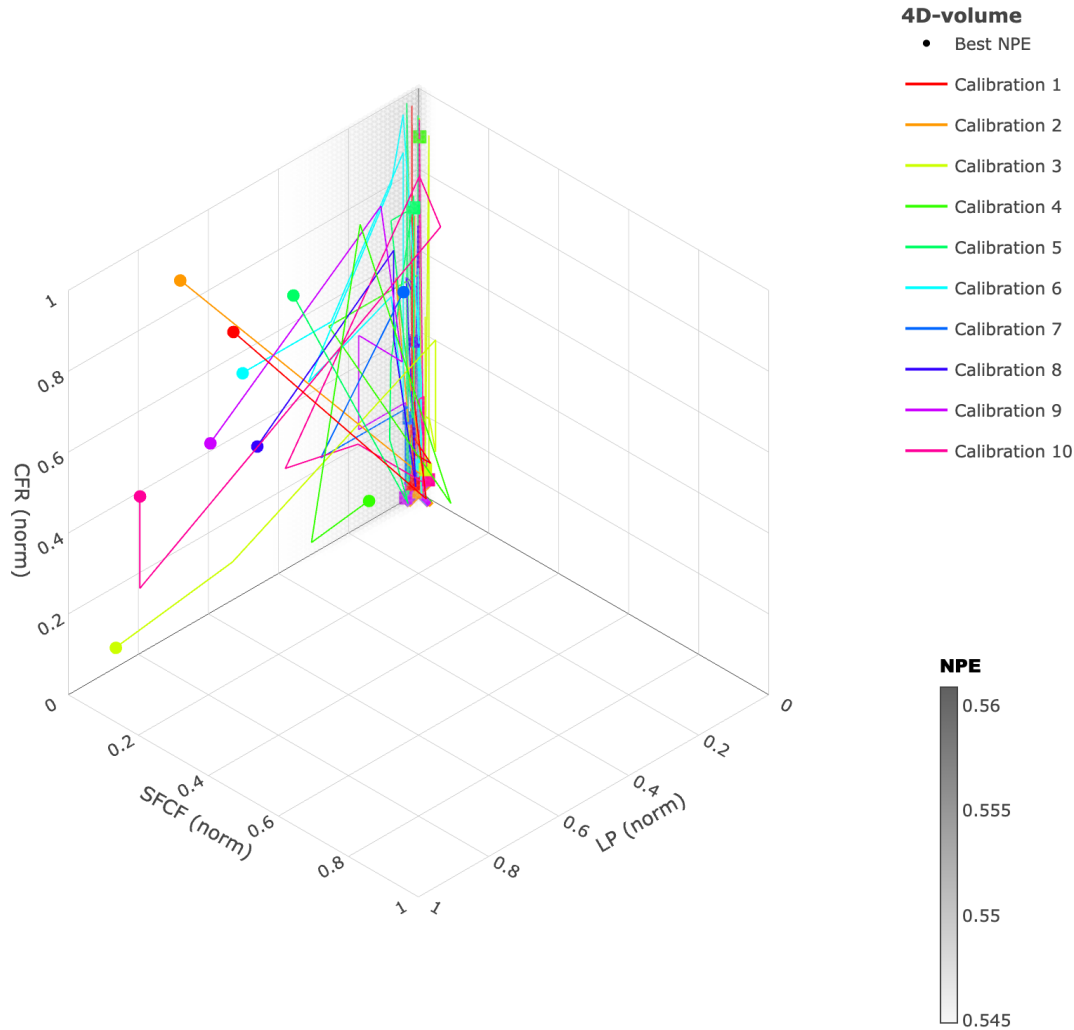
2403_4D_E: Persistence Diagram, top 5%



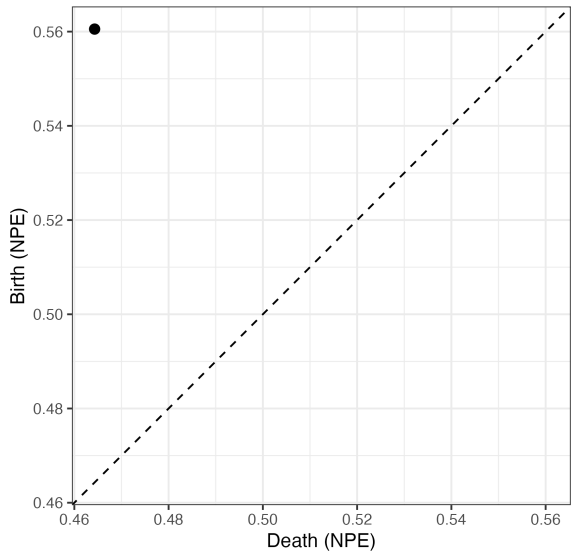
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	-0.03413725	0.38904475	0.3890635	0.38906695	0.63672301
2	0.60544002	0.6054436	0.61108782	0.6111073	0.63672301
3	0.08566214	0.32921594	0.50507289	0.54707557	0.63672301
4	0.26573546	0.3795856	0.37967885	0.37967992	0.63672301
5	0.63260446	0.63537886	0.63541235	0.63541235	0.63672301
6	0.32955327	0.32956661	0.61114882	0.61118099	0.63672301
7	0.20280809	0.20367988	0.20367988	0.54891758	0.63672301
8	0.13399925	0.13454619	0.13486994	0.61907522	0.63672301
9	-0.01397265	-0.01318895	0.35674016	0.35674279	0.63672301
10	0.08748153	0.60901176	0.60902459	0.60906077	0.63672301

2403_4D_J, SFCF_LP_CFR_PERC

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



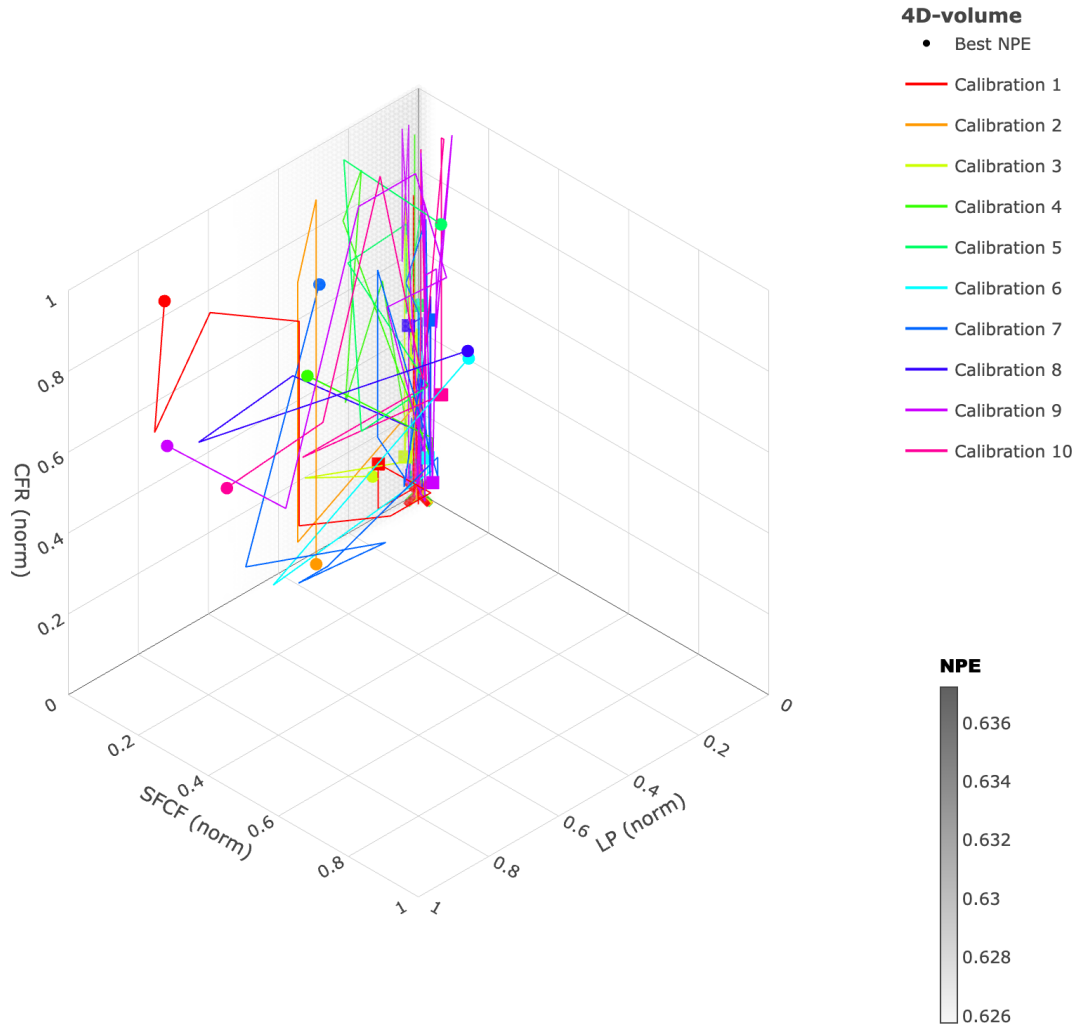
2403_4D_J: Persistence Diagram, top 5%



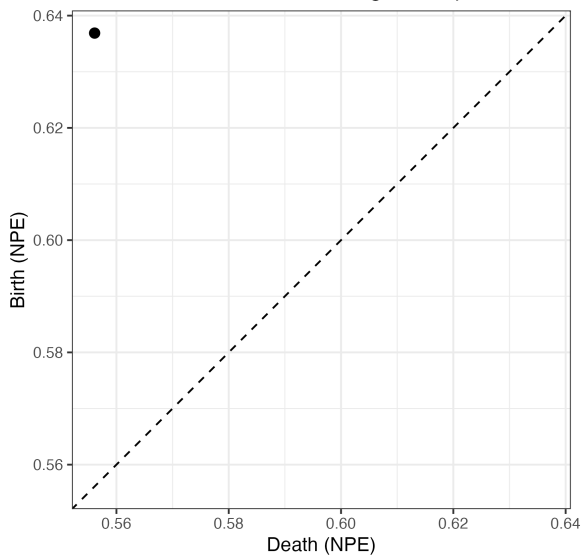
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.55596244	0.56005296	0.56075055	0.5608734	0.56085597
2	0.55824375	0.55980298	0.55980298	0.55981248	0.56085597
3	0.54767779	0.55787484	0.56001831	0.56016688	0.56085597
4	0.55797995	0.56014944	0.5604405	0.5605293	0.56085597
5	0.55129525	0.55983631	0.56074651	0.56087168	0.56085597
6	0.5540908	0.56013584	0.56017544	0.56063984	0.56085597
7	0.55857856	0.56069751	0.56069751	0.5608686	0.56085597
8	0.55770508	0.5607161	0.56082996	0.56091268	0.56085597
9	0.55847153	0.55981911	0.56028134	0.56031641	0.56085597
10	0.54965686	0.55869145	0.56006614	0.56052329	0.56085597

2403_4D_K, SFCF_LP_CFR_PERC

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



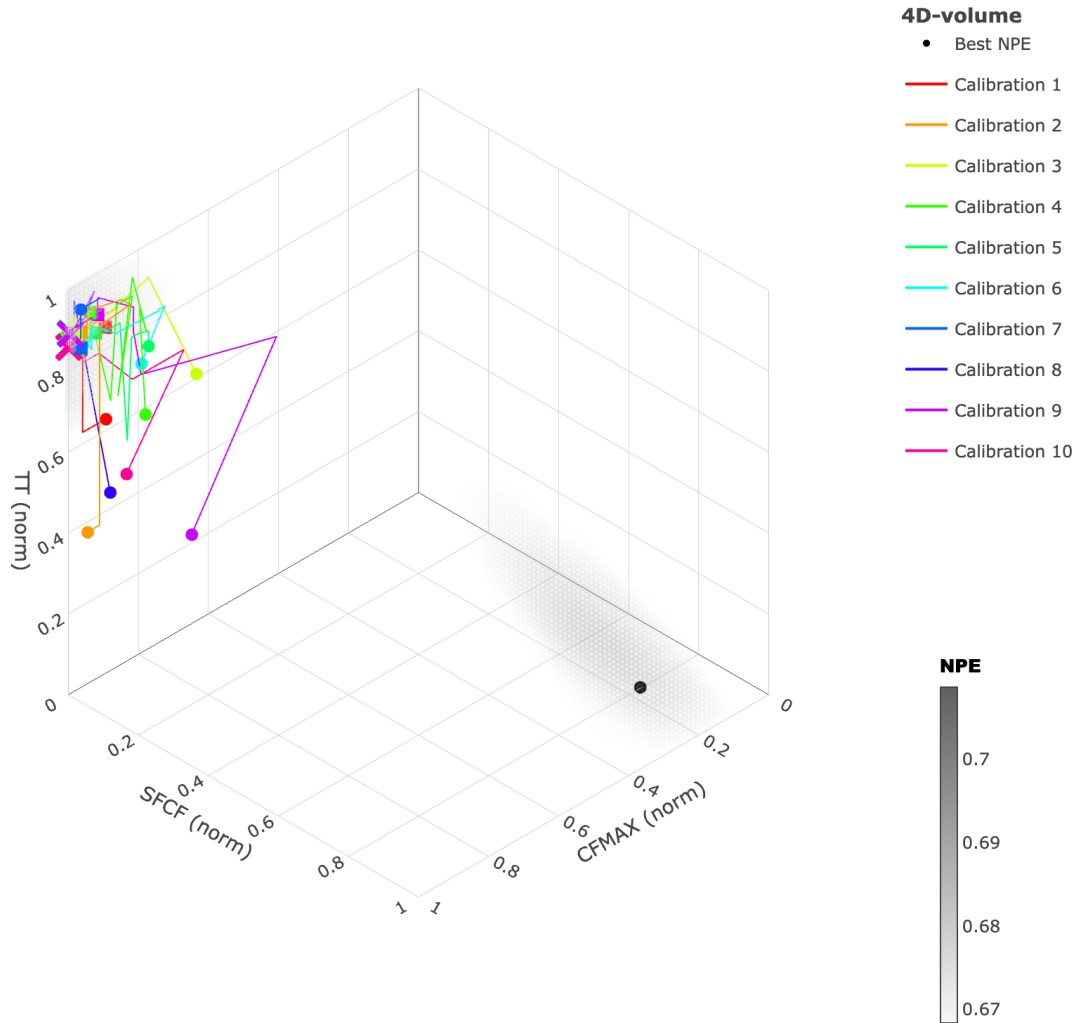
2403_4D_K: Persistence Diagram, top 5%



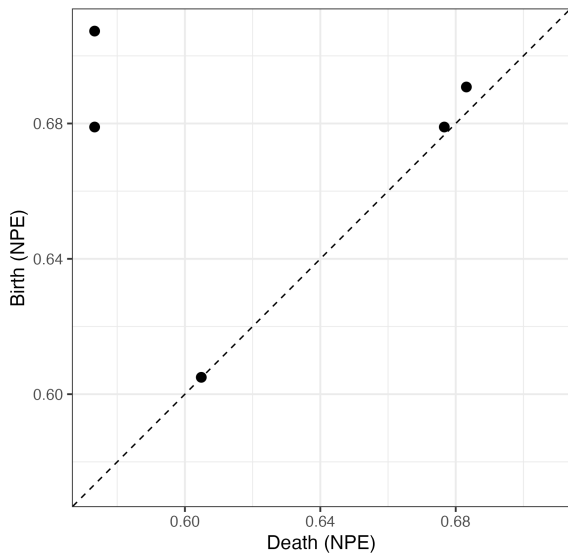
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.62649094	0.63526317	0.63584959	0.636927	0.63722029
2	0.63385955	0.63634406	0.63634406	0.63688216	0.63722029
3	0.62967101	0.63682664	0.63695326	0.63714625	0.63722029
4	0.63673783	0.63713605	0.63740572	0.63745263	0.63722029
5	0.63537516	0.63688166	0.63696967	0.63697039	0.63722029
6	0.63011399	0.63652407	0.63691636	0.63752059	0.63722029
7	0.62456963	0.63693796	0.63723586	0.63756725	0.63722029
8	0.63040816	0.63467554	0.63487267	0.6375487	0.63722029
9	0.61420123	0.63601459	0.636764	0.63716362	0.63722029
10	0.6160783	0.63458681	0.63649207	0.63739892	0.63722029

2426_4D_A, SFCF_CFMAX_TT_K2

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



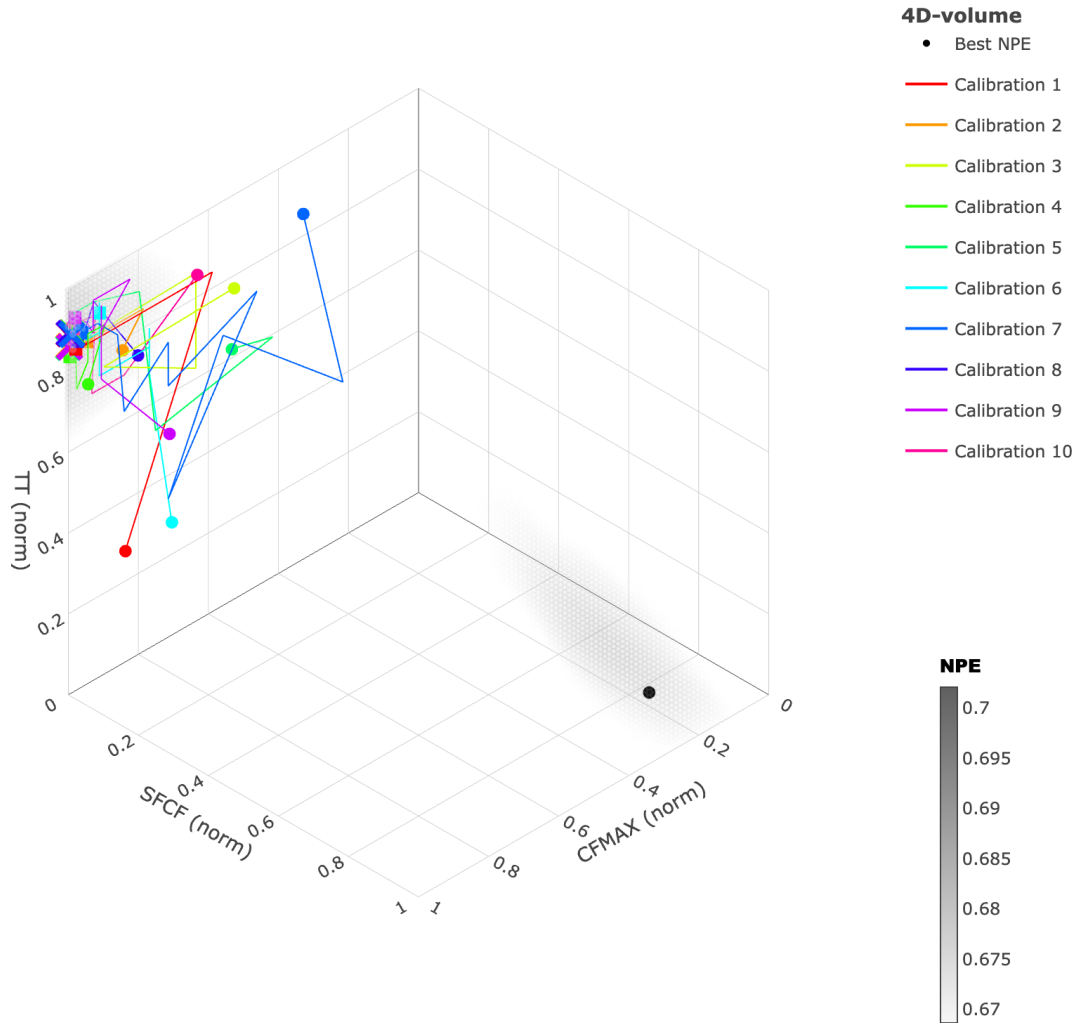
2426_4D_A: Persistence Diagram, top 5%



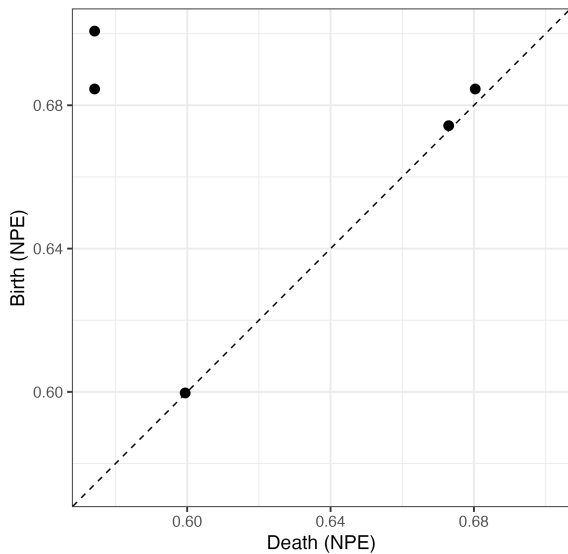
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.67509683	0.67768378	0.68150066	0.68184215	0.70860675
2	0.67123509	0.67940875	0.67941791	0.68164201	0.70860675
3	0.67482459	0.6753344	0.68228729	0.68258237	0.70860675
4	0.67350112	0.6773102	0.67984154	0.68190803	0.70860675
5	0.6720344	0.67355069	0.67451633	0.68277098	0.70860675
6	0.67683799	0.67787287	0.68157244	0.68188311	0.70860675
7	0.6679174	0.68167016	0.68201797	0.68214795	0.70860675
8	0.68006787	0.68010497	0.68085971	0.68263861	0.70860675
9	0.66927418	0.67866666	0.67885961	0.68026809	0.70860675
10	0.67880131	0.68100615	0.68129423	0.6817626	0.70860675

2426_4D_B, SFCF_CFMAX_TT_K2

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



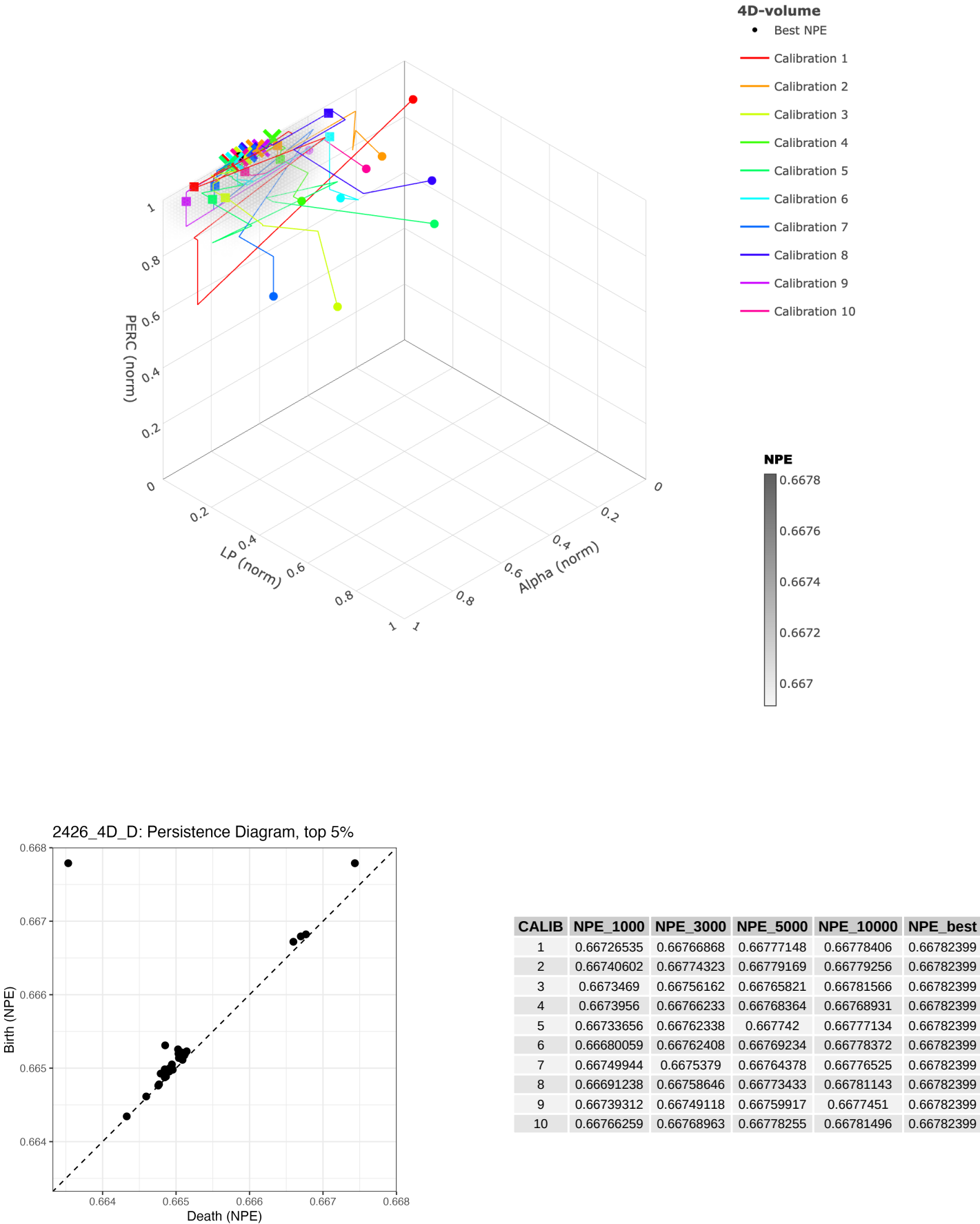
2426_4D_B: Persistence Diagram, top 5%



CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.67474205	0.68382711	0.68382811	0.68404698	0.70203592
2	0.67712467	0.68095913	0.68406508	0.68439052	0.70203592
3	0.68409749	0.68411147	0.68461238	0.68467642	0.70203592
4	0.68072162	0.68133424	0.68169184	0.68396482	0.70203592
5	0.6820163	0.68302774	0.68309424	0.68450087	0.70203592
6	0.66923903	0.68328747	0.68384425	0.68421992	0.70203592
7	0.67293462	0.67683302	0.67686124	0.67881812	0.70203592
8	0.67711247	0.67941964	0.68339233	0.68382554	0.70203592
9	0.67818547	0.68003254	0.68039161	0.68284425	0.70203592
10	0.68307964	0.68374778	0.68374855	0.68424274	0.70203592

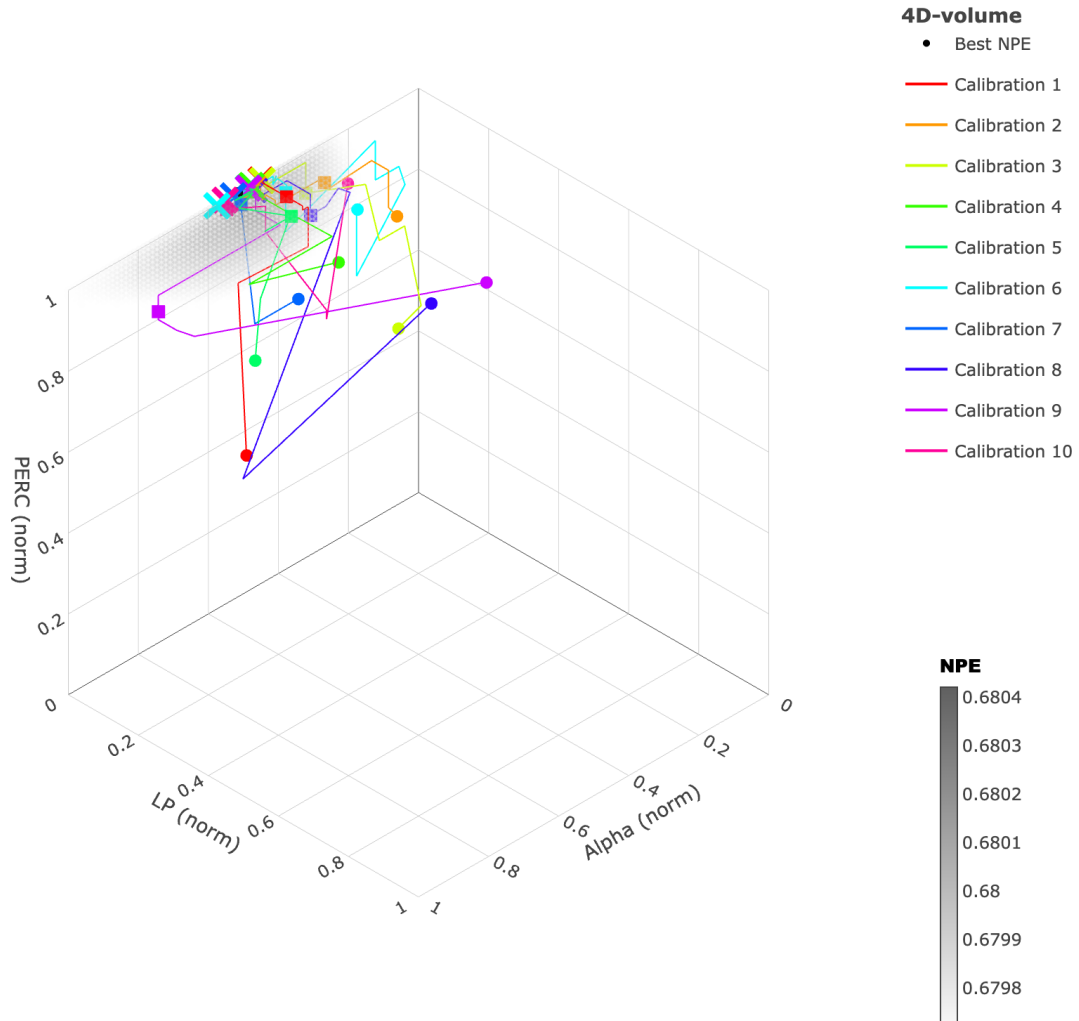
2426_4D_D, LP_Alpha_PERC_K1

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs

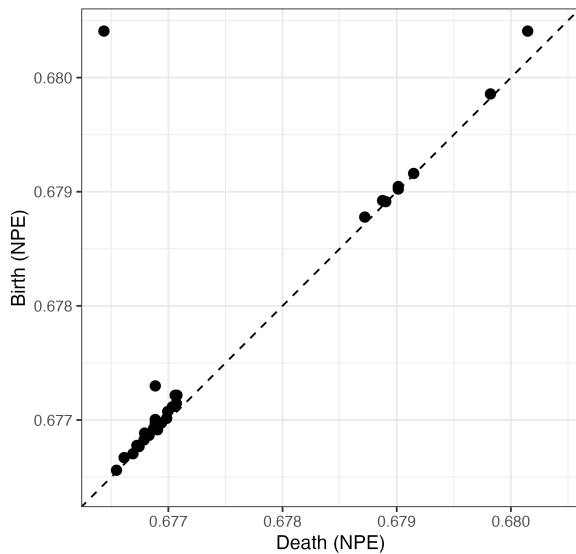


2426_4D_E, LP_Alpha_PERC_K1

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



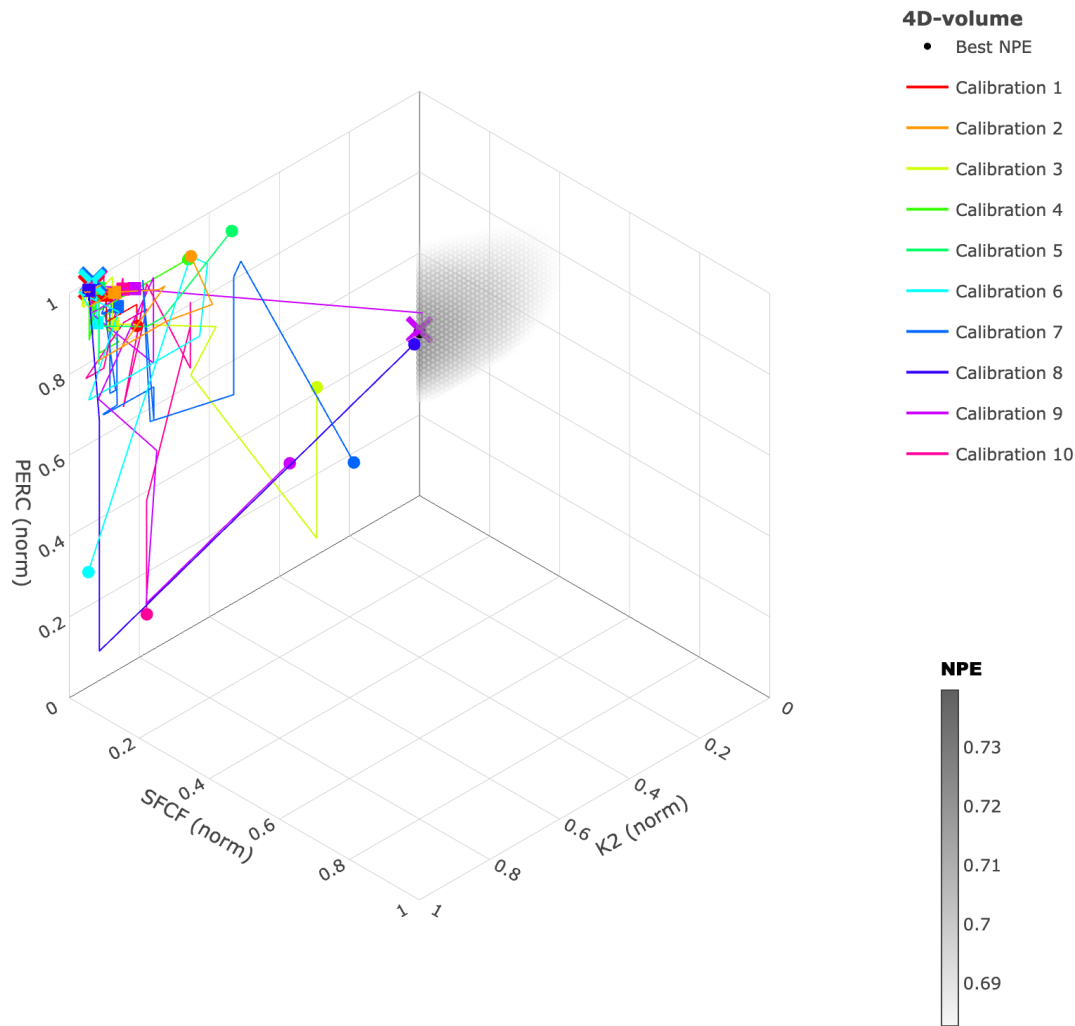
2426_4D_E: Persistence Diagram, top 5%



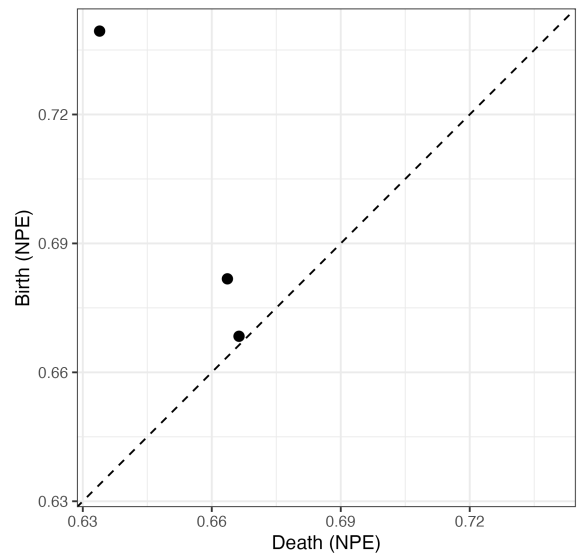
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.68020337	0.68037436	0.68038195	0.68039865	0.68042061
2	0.67994717	0.68031305	0.68036443	0.68041064	0.68042061
3	0.67989322	0.68034462	0.68037291	0.68039332	0.68042061
4	0.6803703	0.68039859	0.68040622	0.68042462	0.68042061
5	0.68008988	0.68039569	0.68040742	0.68042231	0.68042061
6	0.68021311	0.68029475	0.68036628	0.68039183	0.68042061
7	0.68034561	0.68035681	0.6804038	0.68041714	0.68042061
8	0.67982135	0.680271	0.68031423	0.68039054	0.68042061
9	0.67962295	0.68036892	0.68040141	0.68042037	0.68042061
10	0.68036208	0.6804013	0.68040501	0.68041905	0.68042061

2426_4D_J, SFCF_K2_PERC_MAXBAS

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



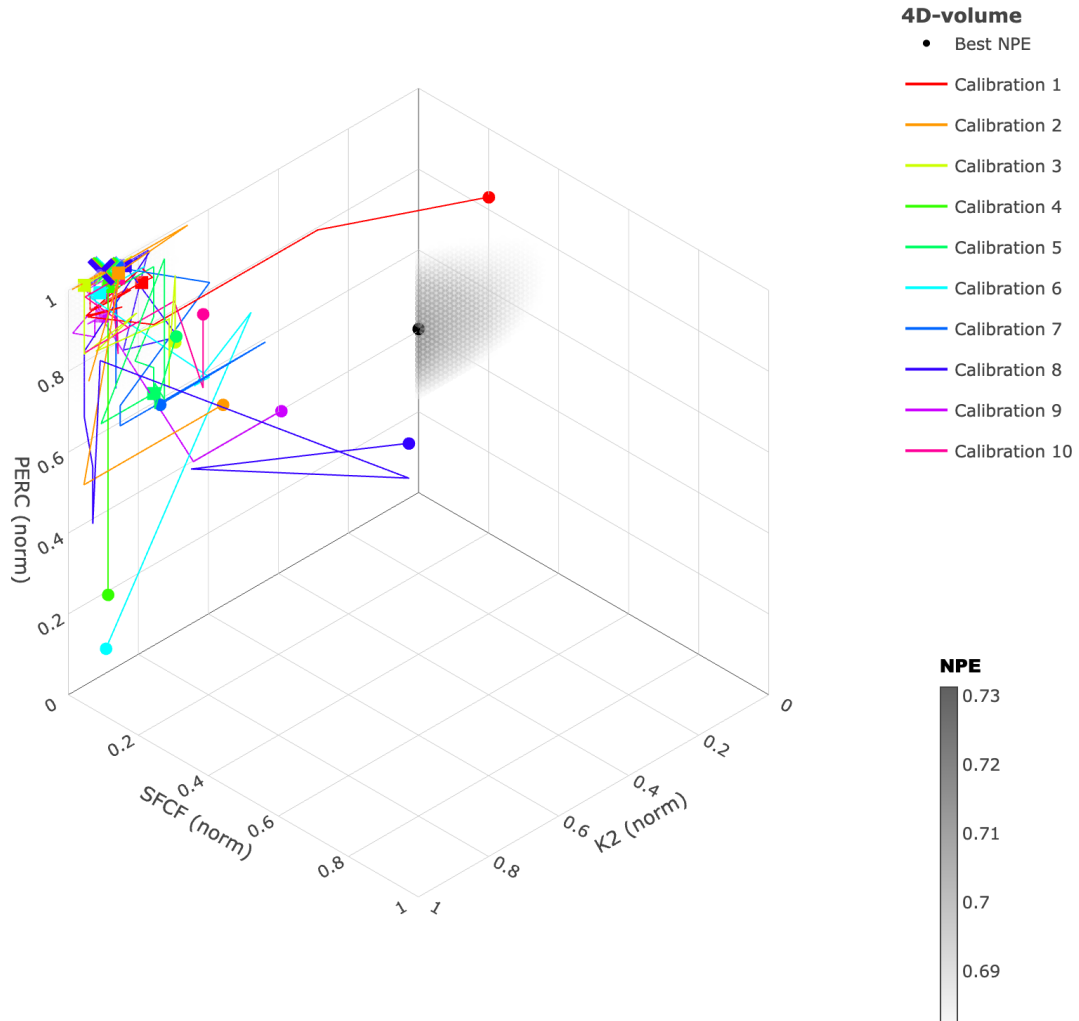
2426_4D_J: Persistence Diagram, top 5%



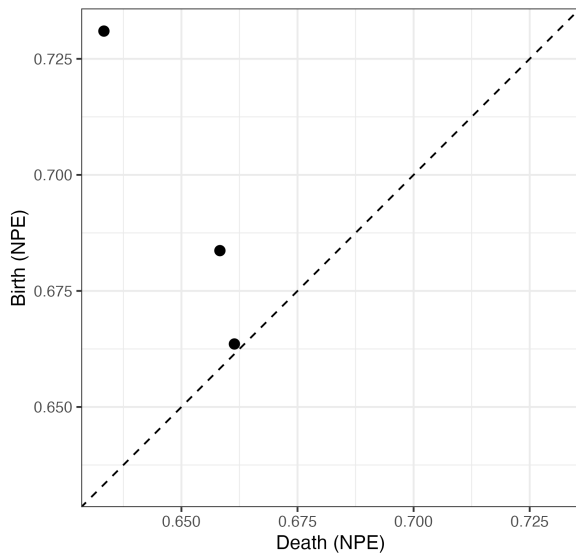
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.67850994	0.68125648	0.68127851	0.68128614	0.73960427
2	0.67131509	0.68207027	0.68210347	0.68211717	0.73960427
3	0.67878497	0.68042893	0.68044069	0.68206079	0.73960427
4	0.68079893	0.68129712	0.68129944	0.68211193	0.73960427
5	0.67343465	0.68210125	0.68210678	0.68210678	0.73960427
6	0.67682408	0.67693283	0.68123247	0.6812452	0.73960427
7	0.67811647	0.68048122	0.68052981	0.68201721	0.73960427
8	0.6734726	0.67440889	0.68080745	0.68220536	0.73960427
9	0.67595674	0.72219423	0.7274493	0.73004775	0.73960427
10	0.68002346	0.68044795	0.68044822	0.68044822	0.73960427

2426_4D_K, SFCF_K2_PERC_MAXBAS

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



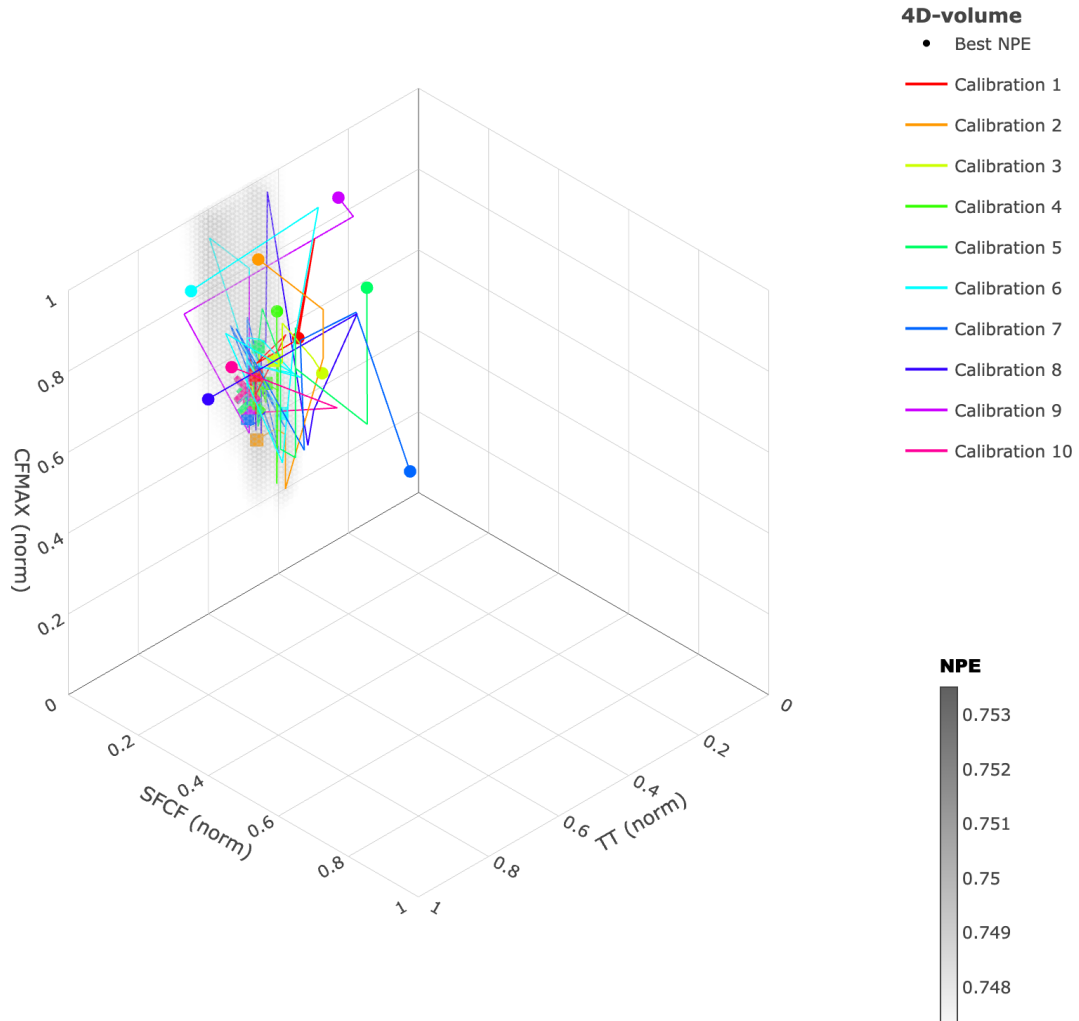
2426_4D_K: Persistence Diagram, top 5%



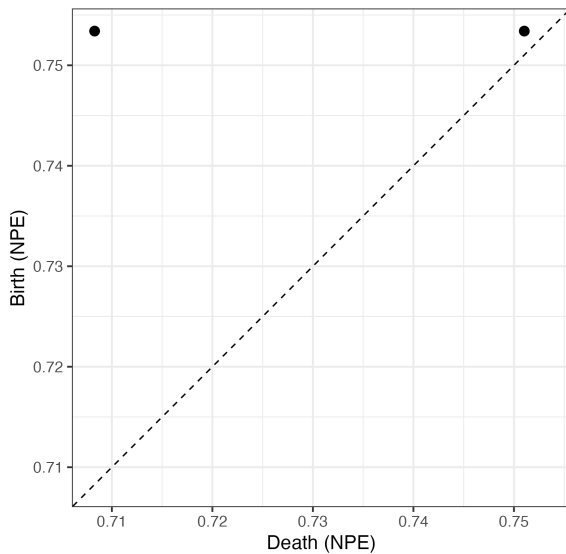
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.67818753	0.68399046	0.68399413	0.68399651	0.73123345
2	0.66686536	0.6794889	0.67949143	0.68353215	0.73123345
3	0.67840474	0.68202026	0.68204552	0.68204552	0.73123345
4	0.6754875	0.68282253	0.68283458	0.6833745	0.73123345
5	0.67657195	0.67866589	0.6786867	0.68156543	0.73123345
6	0.67440973	0.68114876	0.68154102	0.68197845	0.73123345
7	0.67817934	0.67976155	0.68233999	0.68270526	0.73123345
8	0.68055952	0.68368005	0.68368005	0.68398265	0.73123345
9	0.68330112	0.68362126	0.68363508	0.68364906	0.73123345
10	0.67354299	0.67554954	0.68264865	0.68392834	0.73123345

5014_4D_A, SFCF_TT_CFMAX_Alpha

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



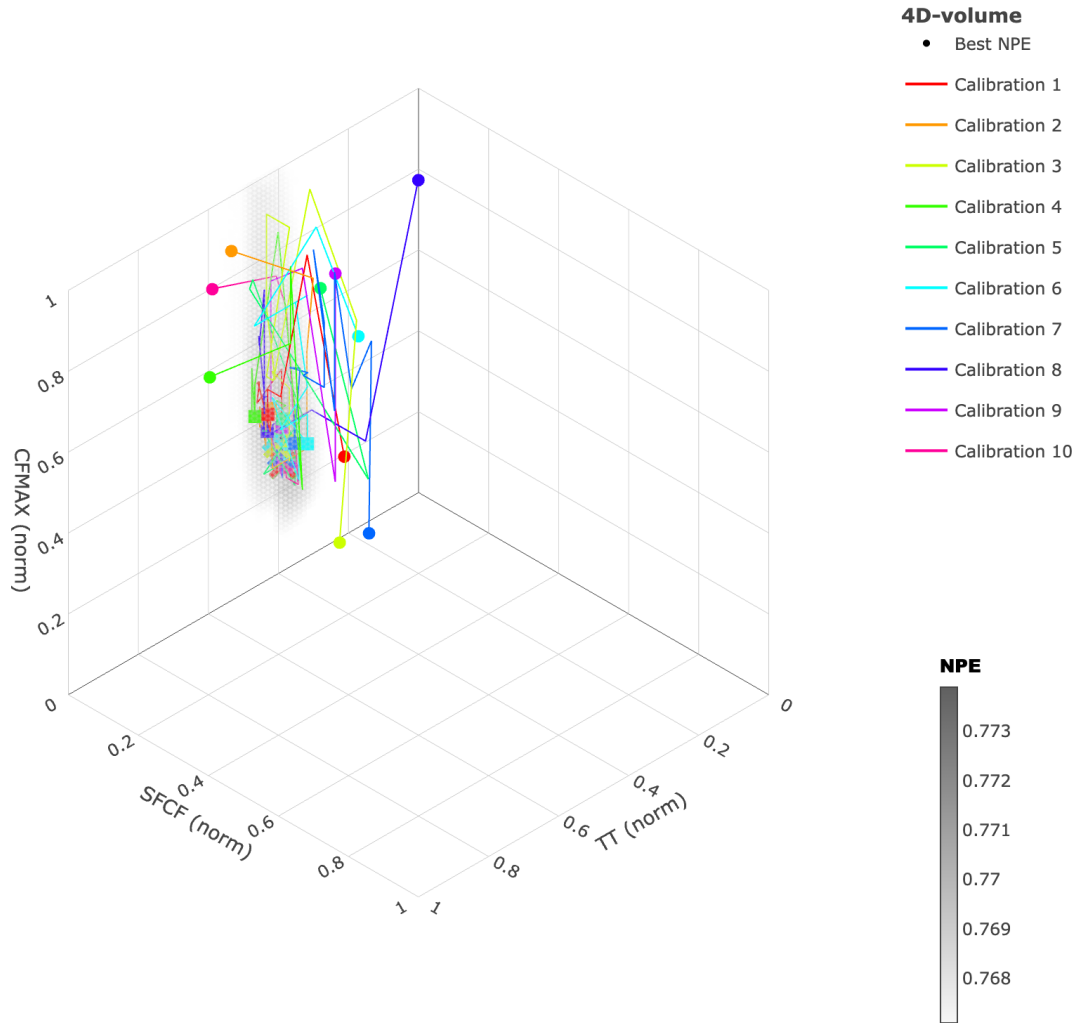
5014_4D_A: Persistence Diagram, top 5%



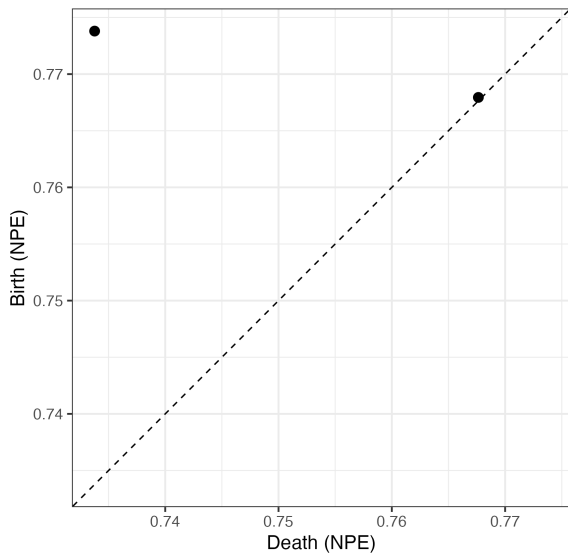
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.75198604	0.75327612	0.75362146	0.75396248	0.75350529
2	0.75237791	0.75291349	0.75343365	0.75361296	0.75350529
3	0.74868103	0.75298819	0.7539822	0.75400007	0.75350529
4	0.7516329	0.75320377	0.753237	0.75352934	0.75350529
5	0.75169046	0.75320128	0.75324497	0.75330824	0.75350529
6	0.74930469	0.75254552	0.75389071	0.75391219	0.75350529
7	0.75243155	0.7538246	0.75386338	0.75395562	0.75350529
8	0.75231894	0.75352005	0.75354679	0.75364285	0.75350529
9	0.75290132	0.75325923	0.75337078	0.75391825	0.75350529
10	0.7533377	0.7538297	0.75386137	0.75396858	0.75350529

5014_4D_B, SFCF_TT_CFMAX_Alpha

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



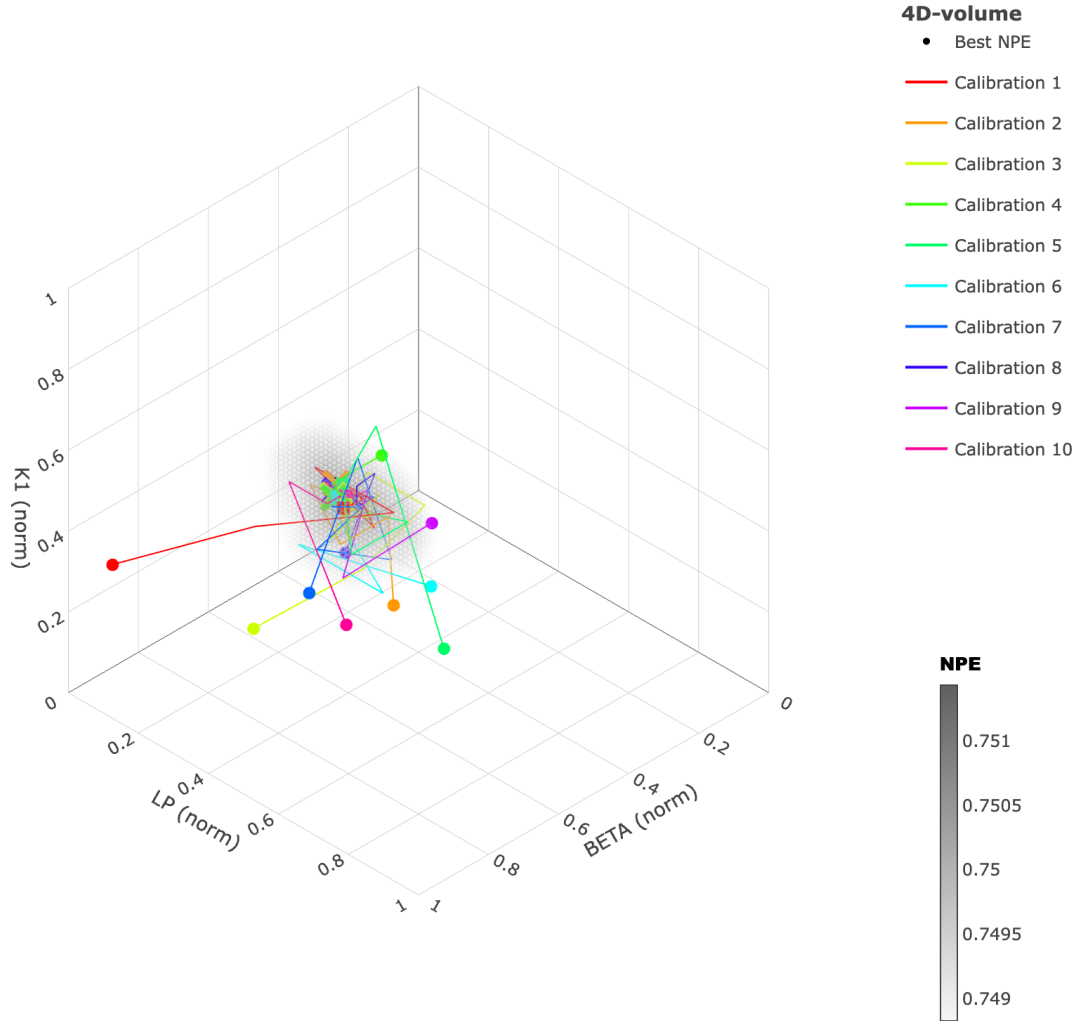
5014_4D_B: Persistence Diagram, top 5%



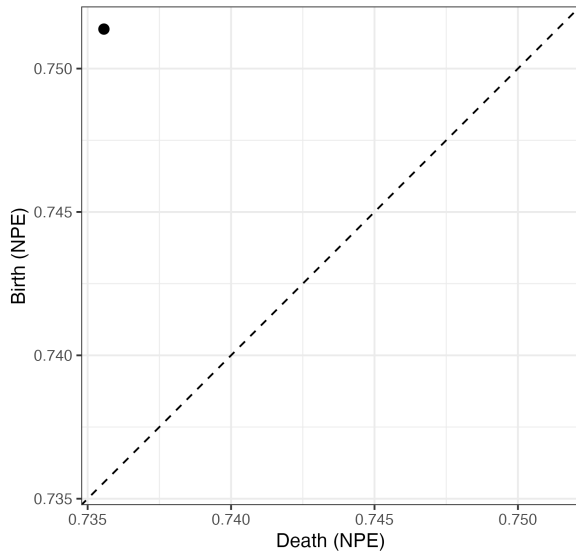
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.77095019	0.77358951	0.77396649	0.77402522	0.77388783
2	0.77132616	0.77395772	0.77400985	0.77401136	0.77388783
3	0.77232576	0.77364231	0.77371387	0.7739543	0.77388783
4	0.77177418	0.77394472	0.7739836	0.77398971	0.77388783
5	0.77255949	0.77302598	0.77375735	0.77395279	0.77388783
6	0.76994786	0.77303356	0.77377842	0.77394705	0.77388783
7	0.77008862	0.77309512	0.77379052	0.77386333	0.77388783
8	0.77182896	0.77339412	0.77377732	0.77381555	0.77388783
9	0.77299274	0.77369271	0.77375942	0.7738052	0.77388783
10	0.77358043	0.77367629	0.7739617	0.77399899	0.77388783

5014_4D_D, LP_BETA_K1_MAXBAS

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



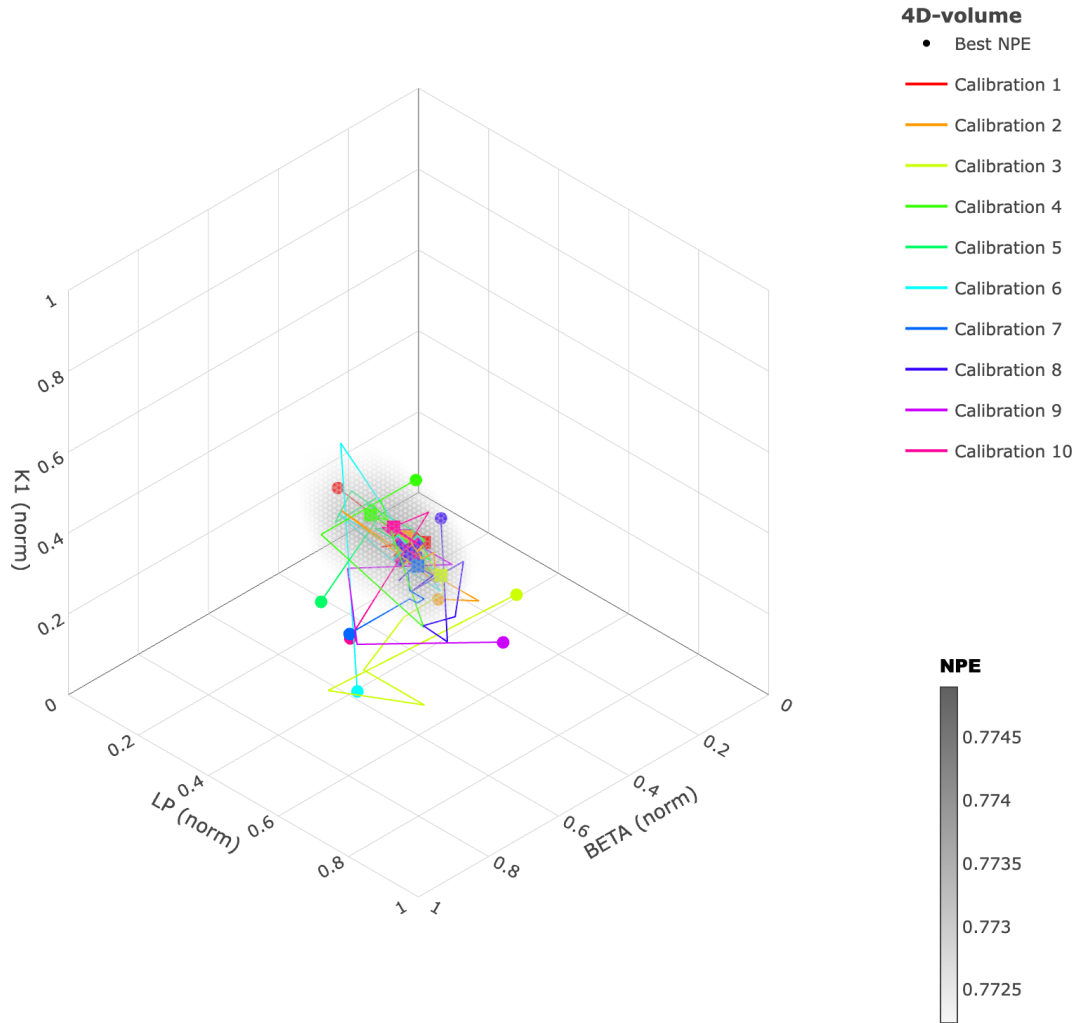
5014_4D_D: Persistence Diagram, top 5%



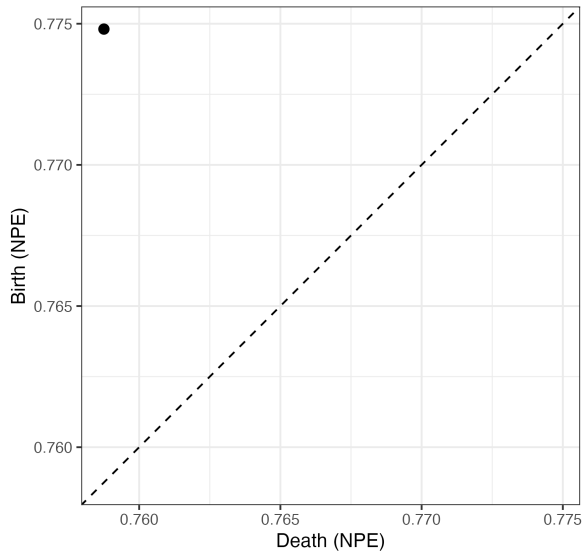
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.75134703	0.7514076	0.7514076	0.751421	0.75142887
2	0.75125441	0.7513318	0.75133421	0.75137856	0.75142887
3	0.75081304	0.75111105	0.75136823	0.75142477	0.75142887
4	0.75141735	0.75143011	0.75143011	0.75143588	0.75142887
5	0.75119555	0.75138781	0.75138792	0.7514078	0.75142887
6	0.75114883	0.75138249	0.75140138	0.75143825	0.75142887
7	0.75138196	0.75141852	0.75142067	0.75142067	0.75142887
8	0.75092541	0.75137797	0.75138407	0.75141516	0.75142887
9	0.75138392	0.75140981	0.75142421	0.75143091	0.75142887
10	0.75114755	0.75128755	0.75134225	0.75139206	0.75142887

5014_4D_E, LP_BETA_K1_MAXBAS

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



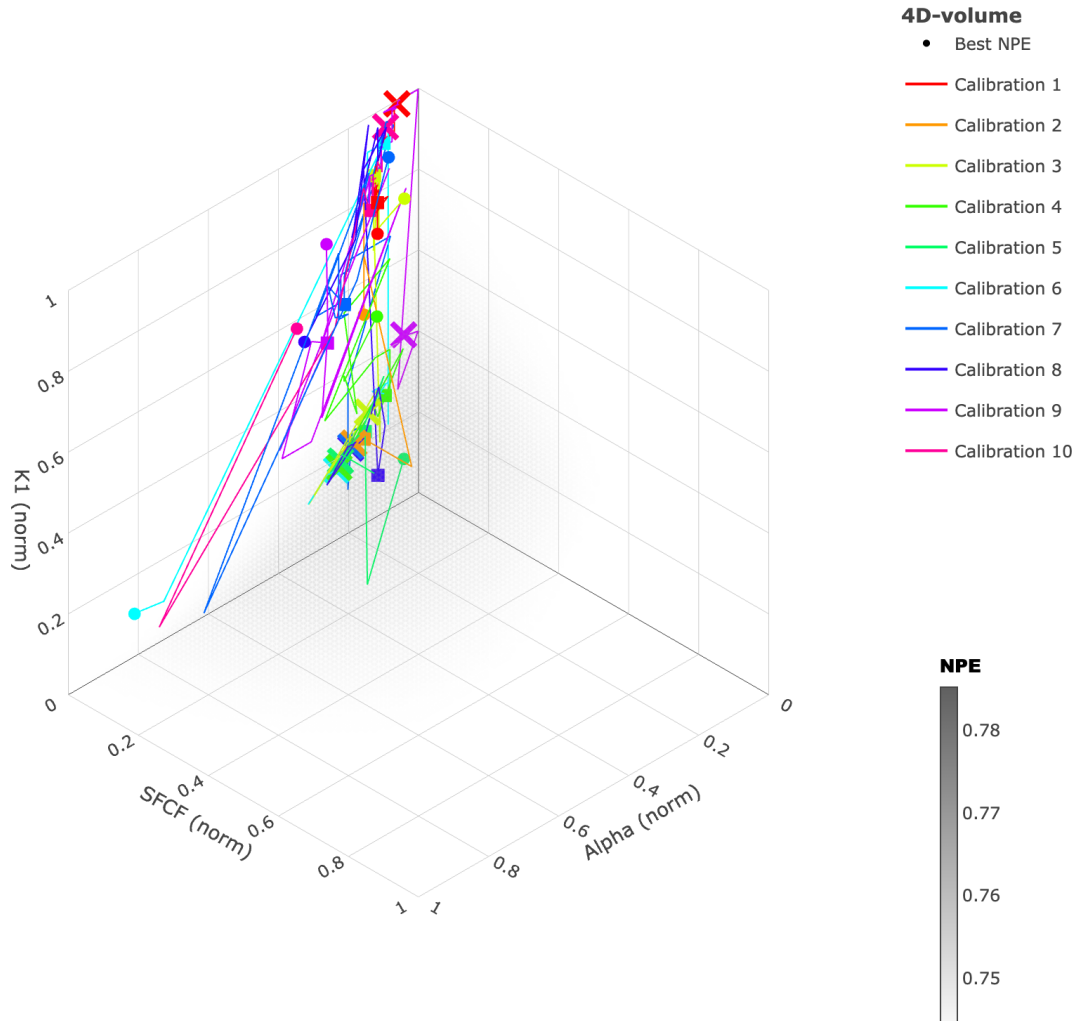
5014_4D_E: Persistence Diagram, top 5%



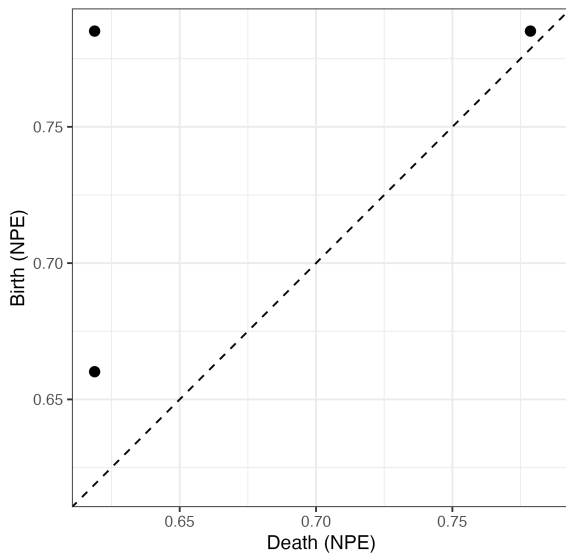
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.77469986	0.77487322	0.77490119	0.77491792	0.77489531
2	0.7742856	0.77478924	0.77484665	0.77484767	0.77489531
3	0.77264004	0.77491166	0.77492354	0.77493109	0.77489531
4	0.77396001	0.77471568	0.77489233	0.77489952	0.77489531
5	0.77457007	0.77486607	0.77486834	0.77490373	0.77489531
6	0.77452107	0.77491668	0.77491668	0.77494559	0.77489531
7	0.77443534	0.77470349	0.77485176	0.7748865	0.77489531
8	0.77444038	0.77478035	0.77478159	0.77494792	0.77489531
9	0.77392023	0.77473914	0.77485309	0.77495678	0.77489531
10	0.77381183	0.7747143	0.77489822	0.77493733	0.77489531

5014_4D_J, SFCF_Alpha_K1_K2

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



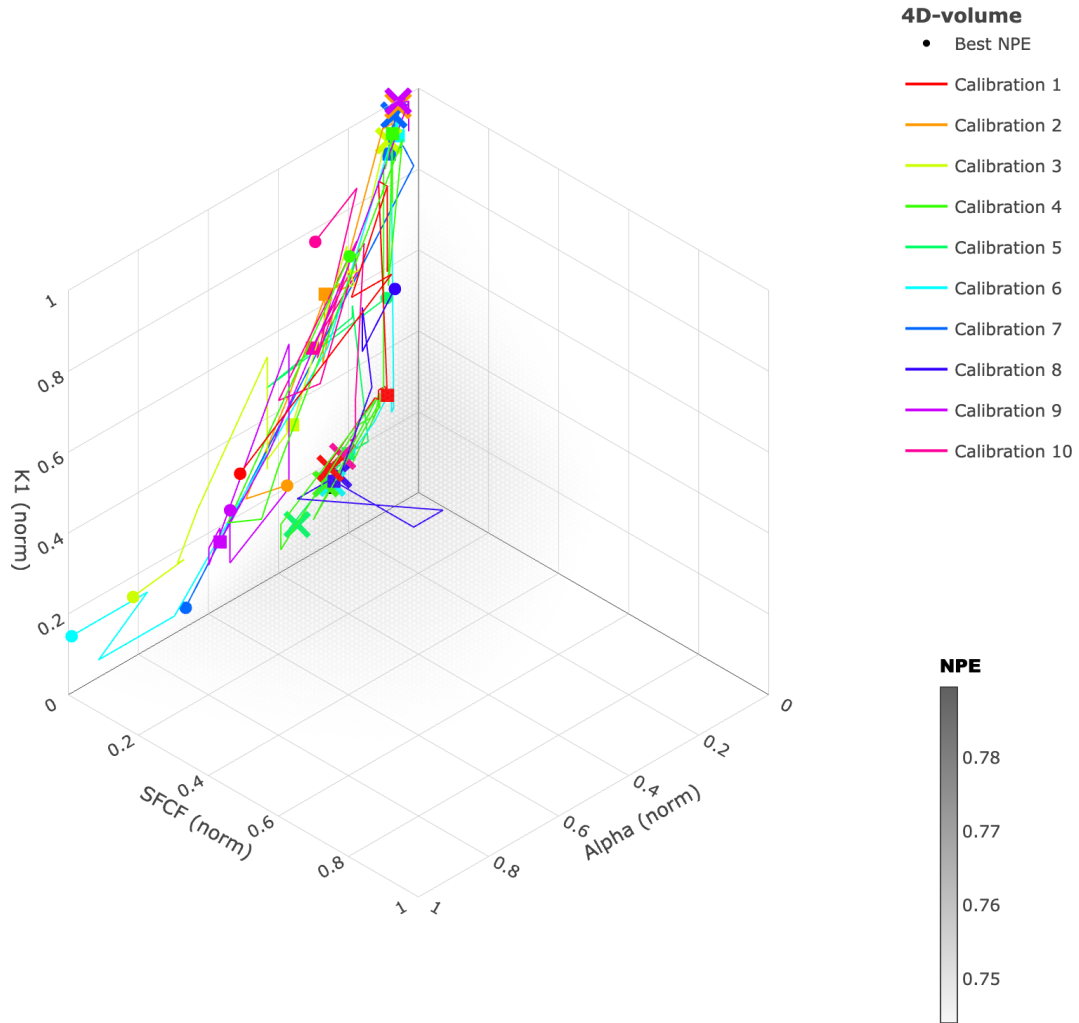
5014_4D_J: Persistence Diagram, top 5%



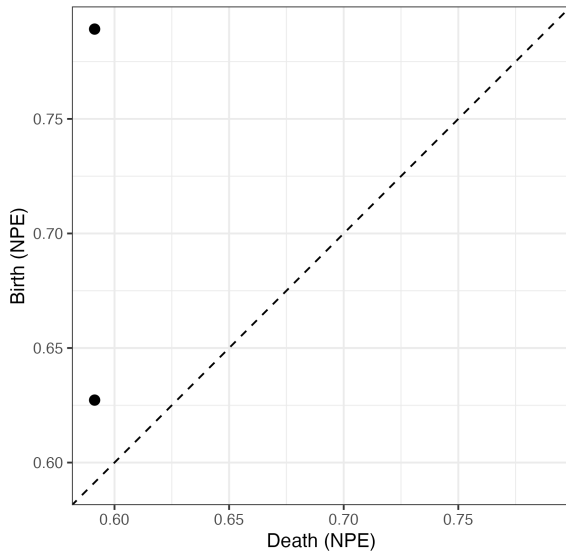
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.65312568	0.6574608	0.65816997	0.66035443	0.78523821
2	0.73633826	0.76411483	0.76414336	0.76433254	0.78523821
3	0.65996376	0.6600188	0.71629944	0.71670422	0.78523821
4	0.73764579	0.73817545	0.76669683	0.76688665	0.78523821
5	0.69055375	0.6912707	0.77947051	0.77948594	0.78523821
6	0.65965561	0.65996707	0.66023906	0.77778315	0.78523821
7	0.65668353	0.65998437	0.74310797	0.76194923	0.78523821
8	0.73320172	0.76451785	0.78372037	0.78389263	0.78523821
9	0.65616292	0.65935754	0.65951859	0.71143031	0.78523821
10	0.65692155	0.65878056	0.65969551	0.6602421	0.78523821

5014_4D_K, SFCF_Alpha_K1_K2

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



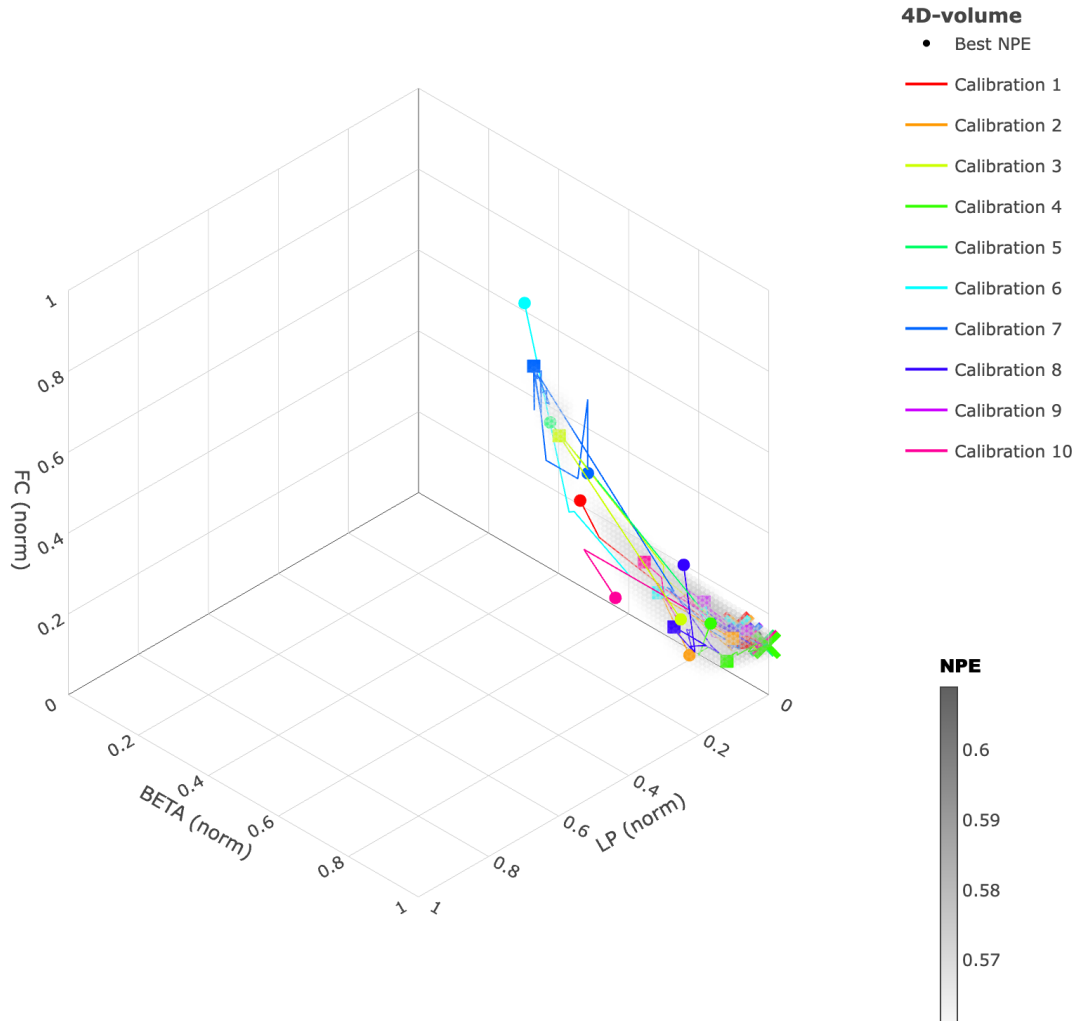
5014_4D_K: Persistence Diagram, top 5%



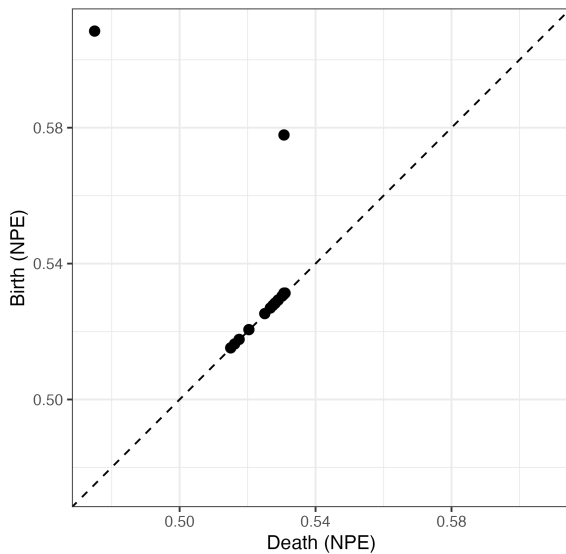
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.63065412	0.63479177	0.63752892	0.63801948	0.78956124
2	0.6266586	0.62763454	0.62801516	0.62808549	0.78956124
3	0.62390413	0.62465436	0.6279402	0.62798484	0.78956124
4	0.62385954	0.69443427	0.69488135	0.7166124	0.78956124
5	0.67976152	0.67992639	0.67993771	0.68019055	0.78956124
6	0.62565997	0.62640821	0.77592674	0.7764202	0.78956124
7	0.62711699	0.62735286	0.62743168	0.62769678	0.78956124
8	0.70069831	0.70172699	0.70172699	0.77029433	0.78956124
9	0.61993162	0.6266225	0.62742689	0.62798629	0.78956124
10	0.62552754	0.65782461	0.65787428	0.68445998	0.78956124

CZ000098_4D_A, BETA_LP_FC_SFCF

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



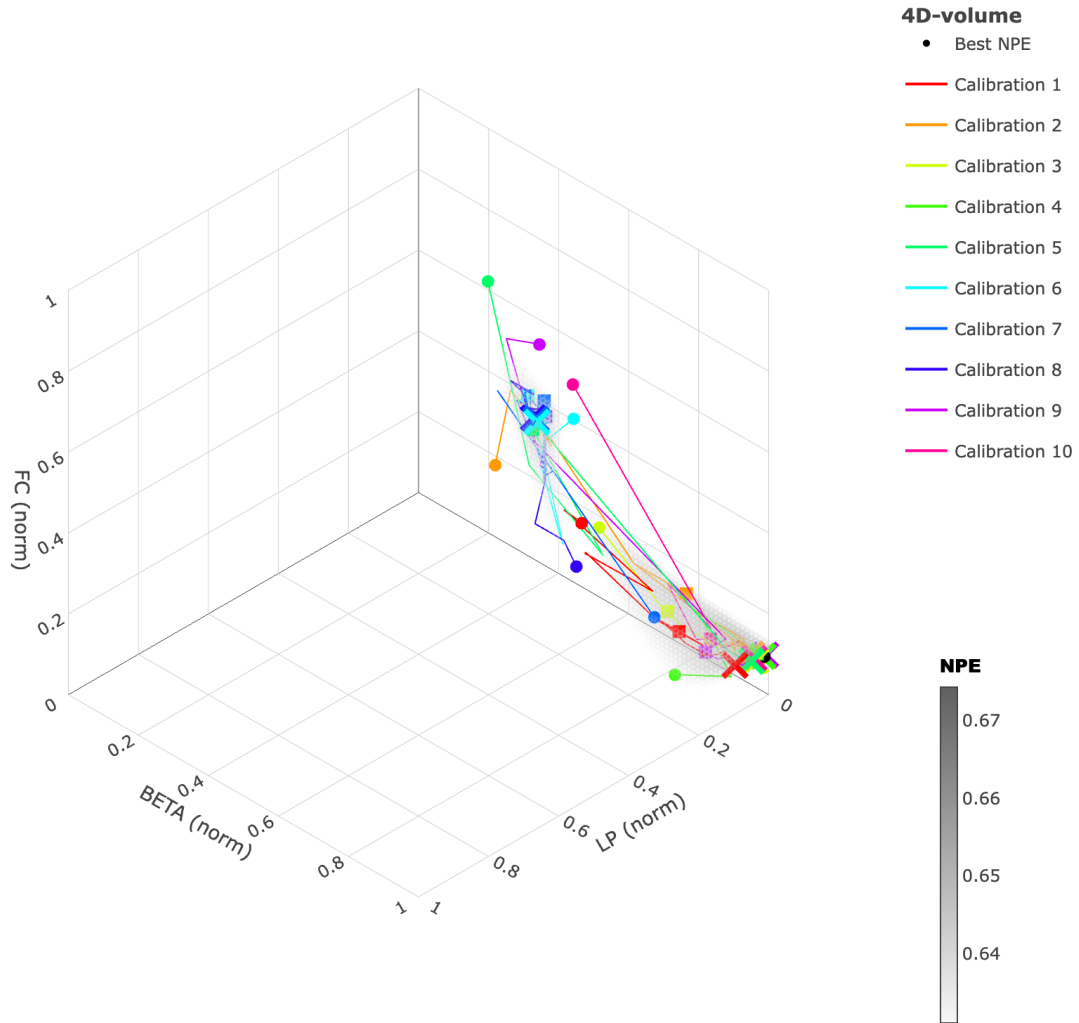
CZ000098_4D_A: Persistence Diagram, top 5%



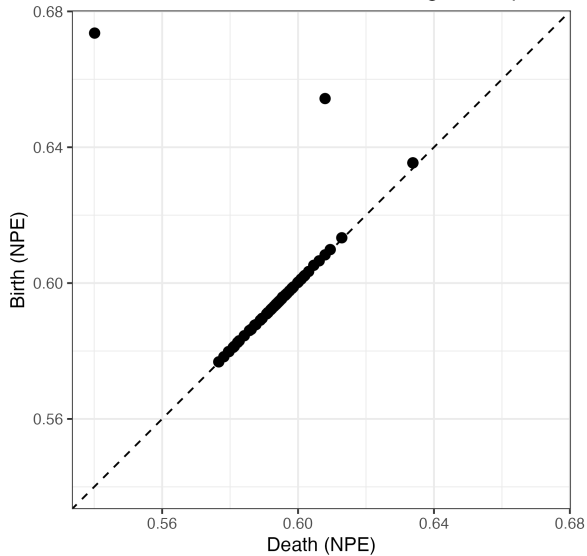
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.60430533	0.60685016	0.60686893	0.60721488	0.60898028
2	0.58611973	0.60676438	0.60678313	0.60772221	0.60898028
3	0.54474997	0.60583223	0.60767737	0.60951751	0.60898028
4	0.59216893	0.60627898	0.60909423	0.6094523	0.60898028
5	0.6050445	0.60829807	0.60834155	0.60949754	0.60898028
6	0.58208635	0.59012079	0.59392915	0.60641103	0.60898028
7	0.5477298	0.56388633	0.59731287	0.60757154	0.60898028
8	0.5673108	0.58292207	0.59145632	0.60576795	0.60898028
9	0.59455746	0.60609647	0.60672243	0.60748876	0.60898028
10	0.57747374	0.60622477	0.60857083	0.60945083	0.60898028

CZ000098_4D_B, BETA_LP_FC_SFCF

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



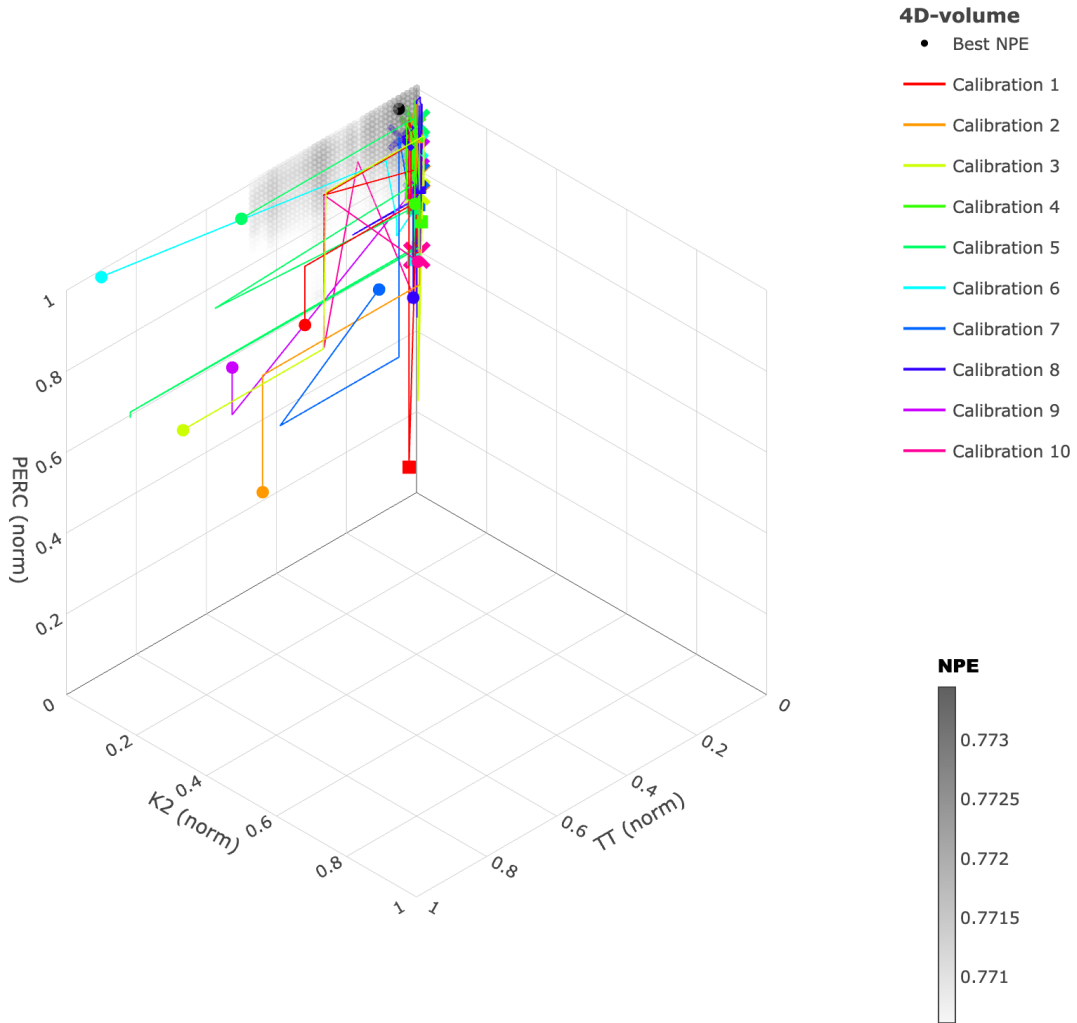
CZ000098_4D_B: Persistence Diagram, top 5%



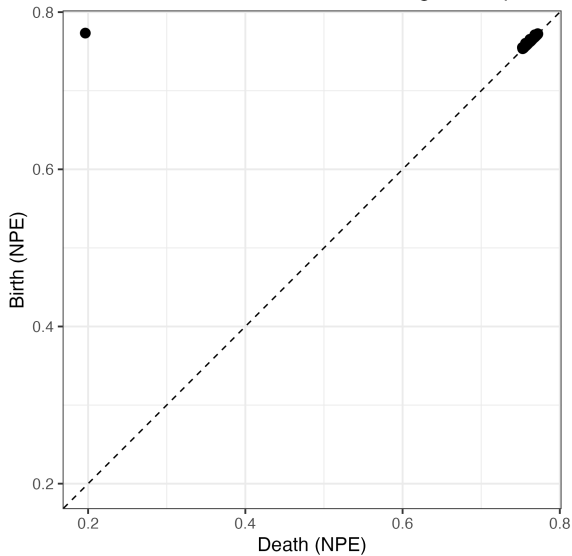
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.63956842	0.65349532	0.6584985	0.66906657	0.67425252
2	0.64188802	0.65965428	0.66626672	0.67324274	0.67425252
3	0.65268361	0.66533604	0.672316	0.67355406	0.67425252
4	0.66869111	0.67175033	0.67238876	0.67472042	0.67425252
5	0.65041474	0.66814116	0.66951511	0.67264067	0.67425252
6	0.63975318	0.65310011	0.65578744	0.65978614	0.67425252
7	0.6390634	0.64126785	0.64983022	0.6595239	0.67425252
8	0.62934968	0.65092235	0.65407162	0.65861131	0.67425252
9	0.6623301	0.66371276	0.6717186	0.67476053	0.67425252
10	0.66738352	0.66782449	0.67187328	0.67285402	0.67425252

CZ000098_4D_D, K2_TT_PERC_CFMAX

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



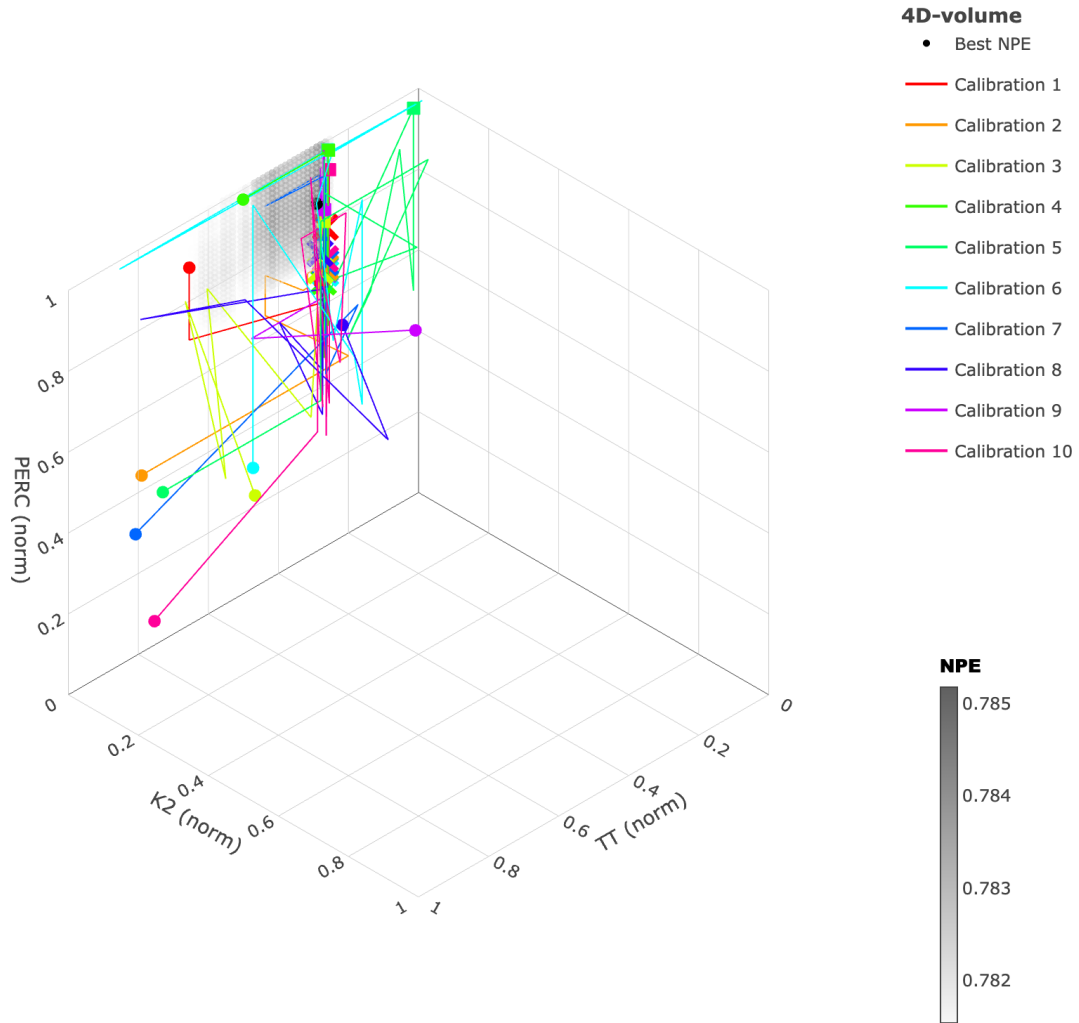
CZ000098_4D_D: Persistence Diagram, top 5%



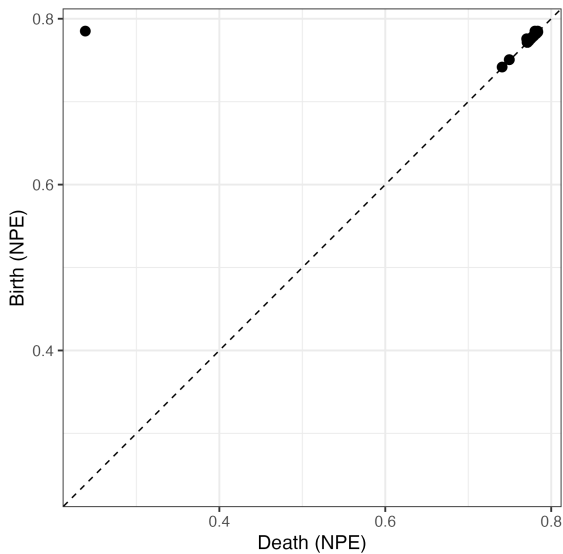
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.53368543	0.7191884	0.71919046	0.77548507	0.77344682
2	0.58737824	0.76701079	0.76775847	0.77504624	0.77344682
3	0.64128749	0.64130905	0.77250922	0.77253924	0.77344682
4	0.40595877	0.77548332	0.77561647	0.77563293	0.77344682
5	0.70704013	0.76821454	0.77560131	0.77599647	0.77344682
6	0.7241666	0.77052743	0.77064901	0.77527645	0.77344682
7	0.699995	0.77534546	0.77547701	0.77561628	0.77344682
8	0.44821872	0.55253143	0.77148179	0.77455923	0.77344682
9	0.76691262	0.76721359	0.76762313	0.77549995	0.77344682
10	0.76831035	0.76906061	0.76913342	0.7691387	0.77344682

CZ000098_4D_E, K2_TT_PERC_CFMAX

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



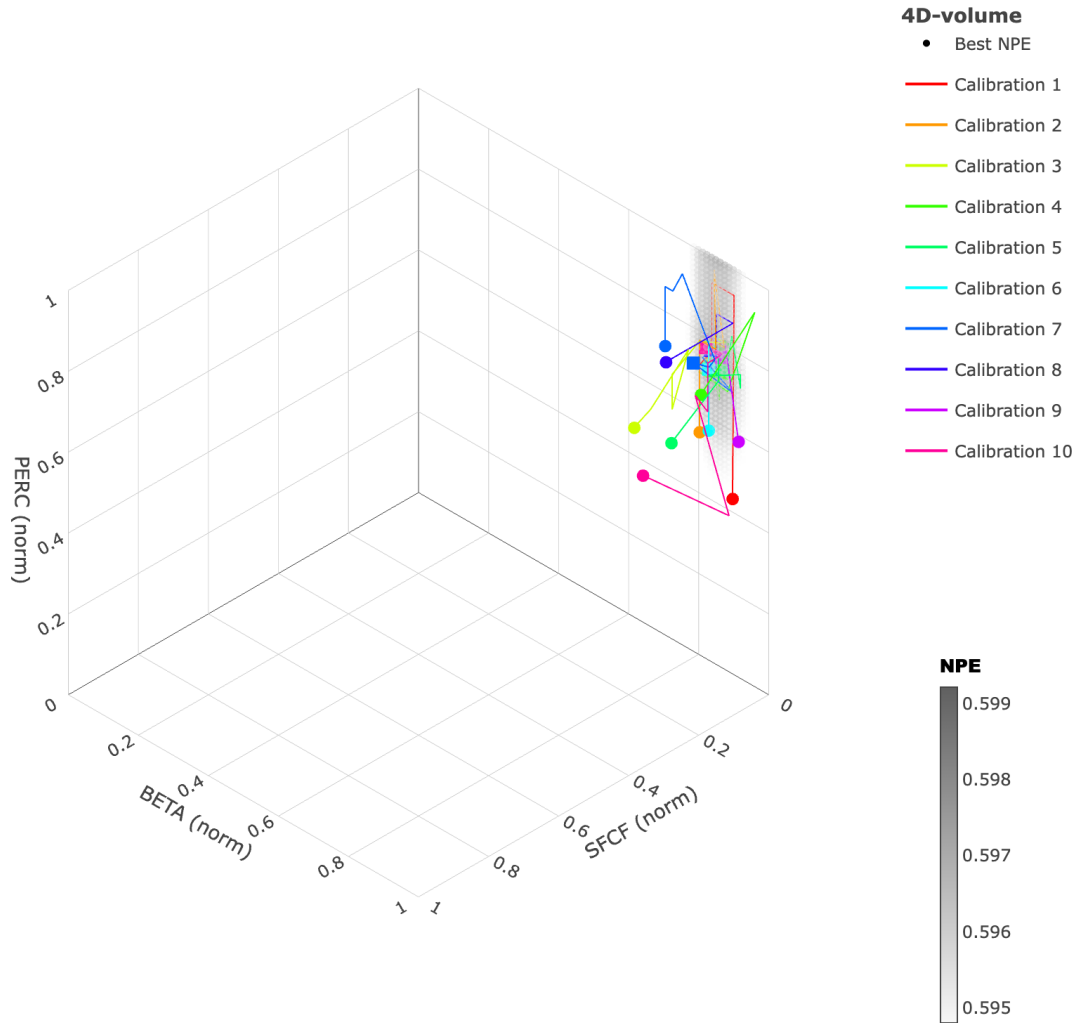
CZ000098_4D_E: Persistence Diagram, top 5%



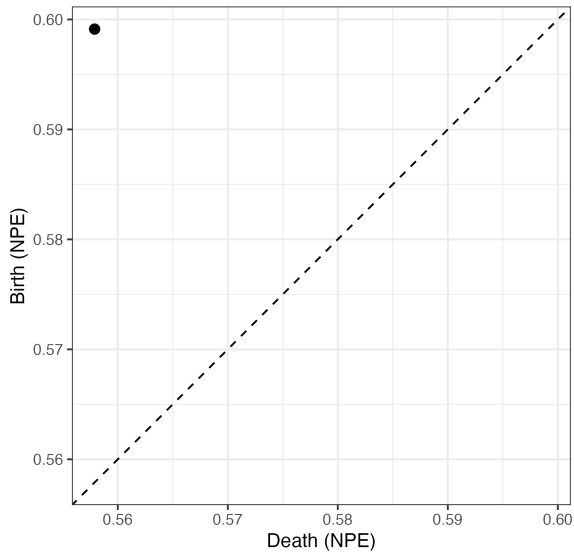
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.77321161	0.78246336	0.78375495	0.78941219	0.7851788
2	0.79229169	0.79325445	0.79338213	0.79340194	0.7851788
3	0.63631651	0.79253923	0.7936374	0.79363871	0.7851788
4	0.54824105	0.78358473	0.78373664	0.79356574	0.7851788
5	0.49769364	0.71352131	0.71354377	0.79341383	0.7851788
6	0.77650034	0.79308985	0.79356767	0.79377961	0.7851788
7	0.7876267	0.78799356	0.78806291	0.79324745	0.7851788
8	0.77477159	0.7752245	0.77524047	0.79022896	0.7851788
9	0.60579656	0.79364119	0.7938277	0.79385361	0.7851788
10	0.61789223	0.78419968	0.79309397	0.79311146	0.7851788

CZ000098_4D_J, BETA_SFCF_PERC_Alpha

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



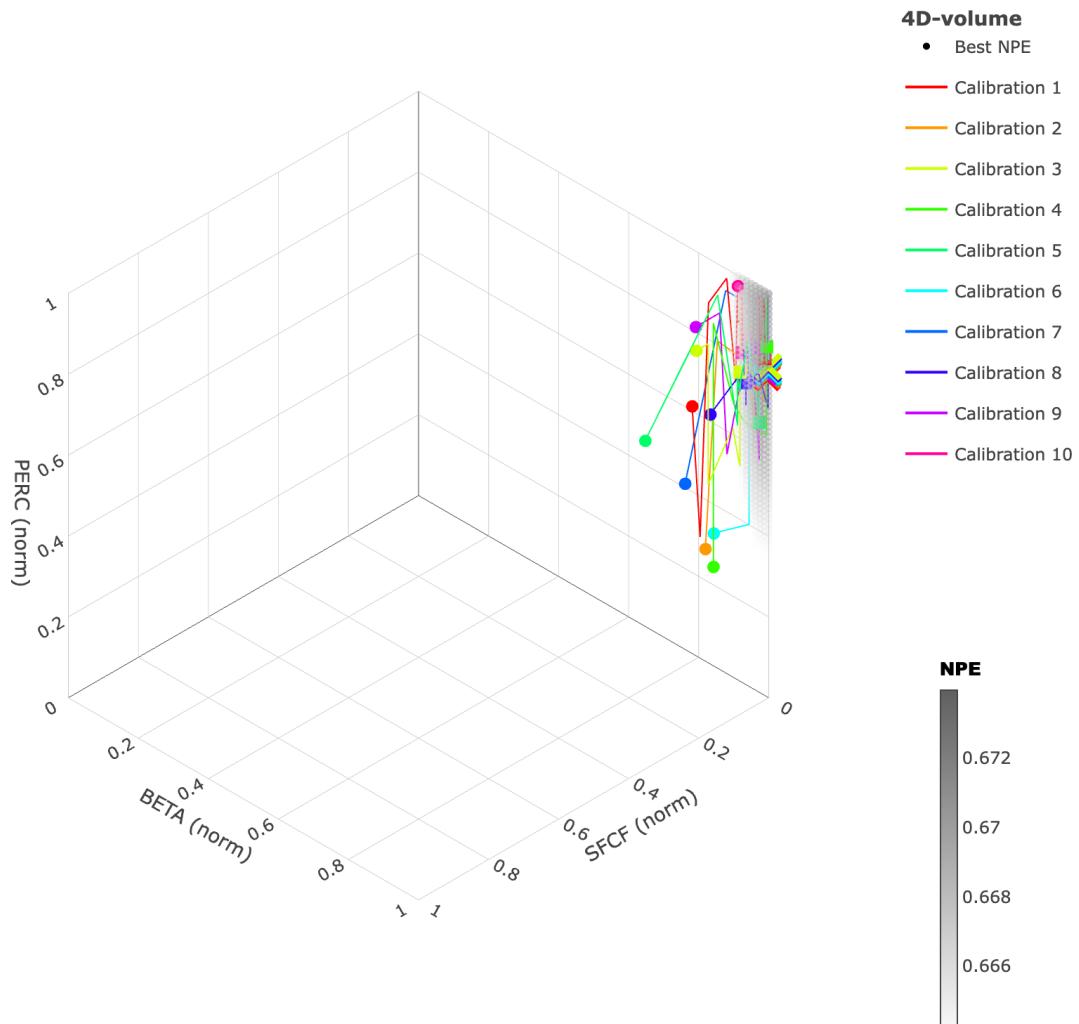
CZ000098_4D_J: Persistence Diagram, top 5%



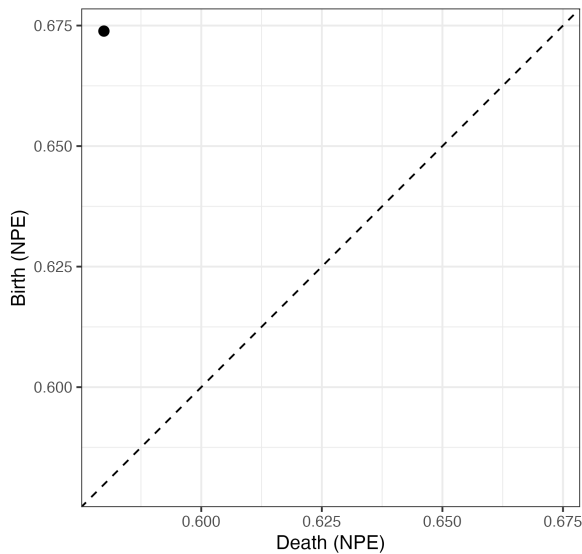
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.59816752	0.59834347	0.59834347	0.59869477	0.59921045
2	0.59800061	0.59912685	0.5991347	0.59914706	0.59921045
3	0.59825853	0.59913028	0.59914996	0.59917585	0.59921045
4	0.5970797	0.59875852	0.59885412	0.5988765	0.59921045
5	0.59741739	0.59839709	0.59877198	0.5989856	0.59921045
6	0.59591784	0.59901334	0.59909086	0.59915313	0.59921045
7	0.5929457	0.59894081	0.59906056	0.59908939	0.59921045
8	0.59745792	0.59900506	0.59907374	0.59908821	0.59921045
9	0.59797239	0.59872173	0.59874228	0.59876569	0.59921045
10	0.59625097	0.59876486	0.59877317	0.59881246	0.59921045

CZ000098_4D_K, BETA_SFCE_PERC_Alpha

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



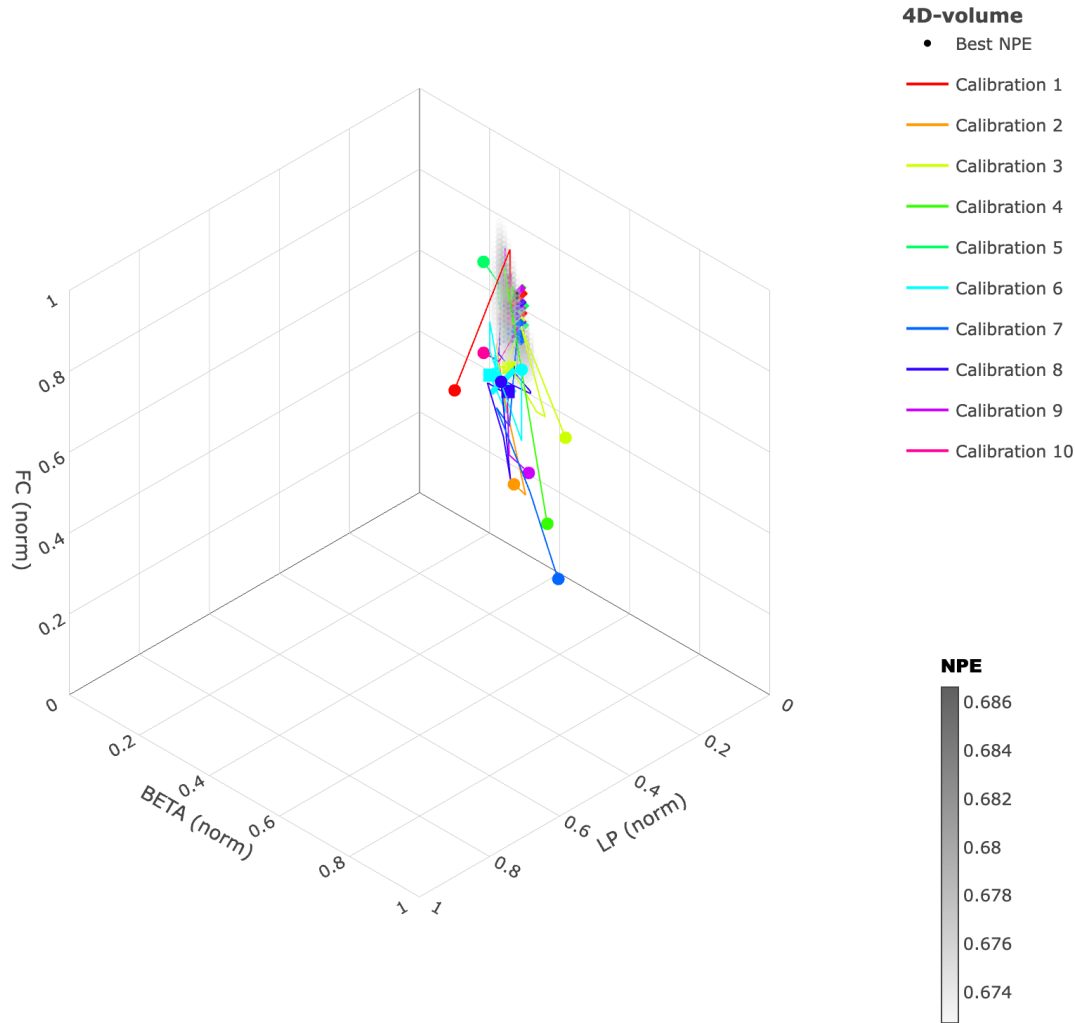
CZ000098_4D_K: Persistence Diagram, top 5%



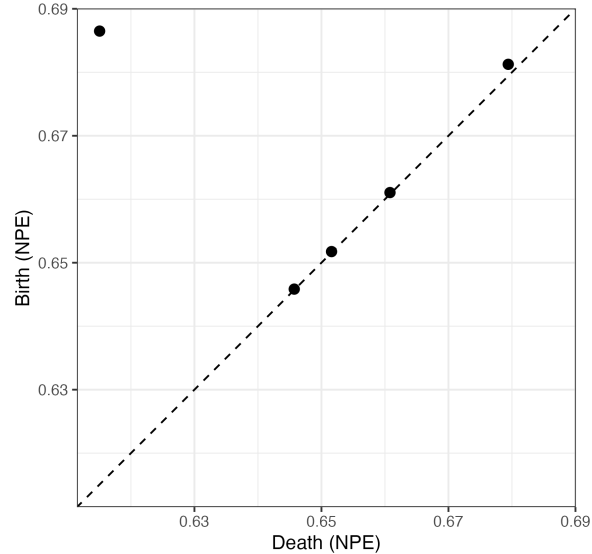
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.67299437	0.67341207	0.67342309	0.6734837	0.67395927
2	0.67104121	0.6732691	0.6732691	0.67380051	0.67395927
3	0.66543695	0.67353118	0.67383897	0.6738414	0.67395927
4	0.67314211	0.67331688	0.67374508	0.67388448	0.67395927
5	0.66976981	0.67338617	0.67370995	0.67372442	0.67395927
6	0.67175981	0.67388239	0.67388626	0.67395459	0.67395927
7	0.67364321	0.67373869	0.67374033	0.6738317	0.67395927
8	0.66725429	0.67071133	0.67376199	0.6738877	0.67395927
9	0.67131308	0.67260077	0.67296717	0.67316501	0.67395927
10	0.66844881	0.67333232	0.67364742	0.67379192	0.67395927

DEBB0132_4D_A, BETA_LP_FC_SFCF

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



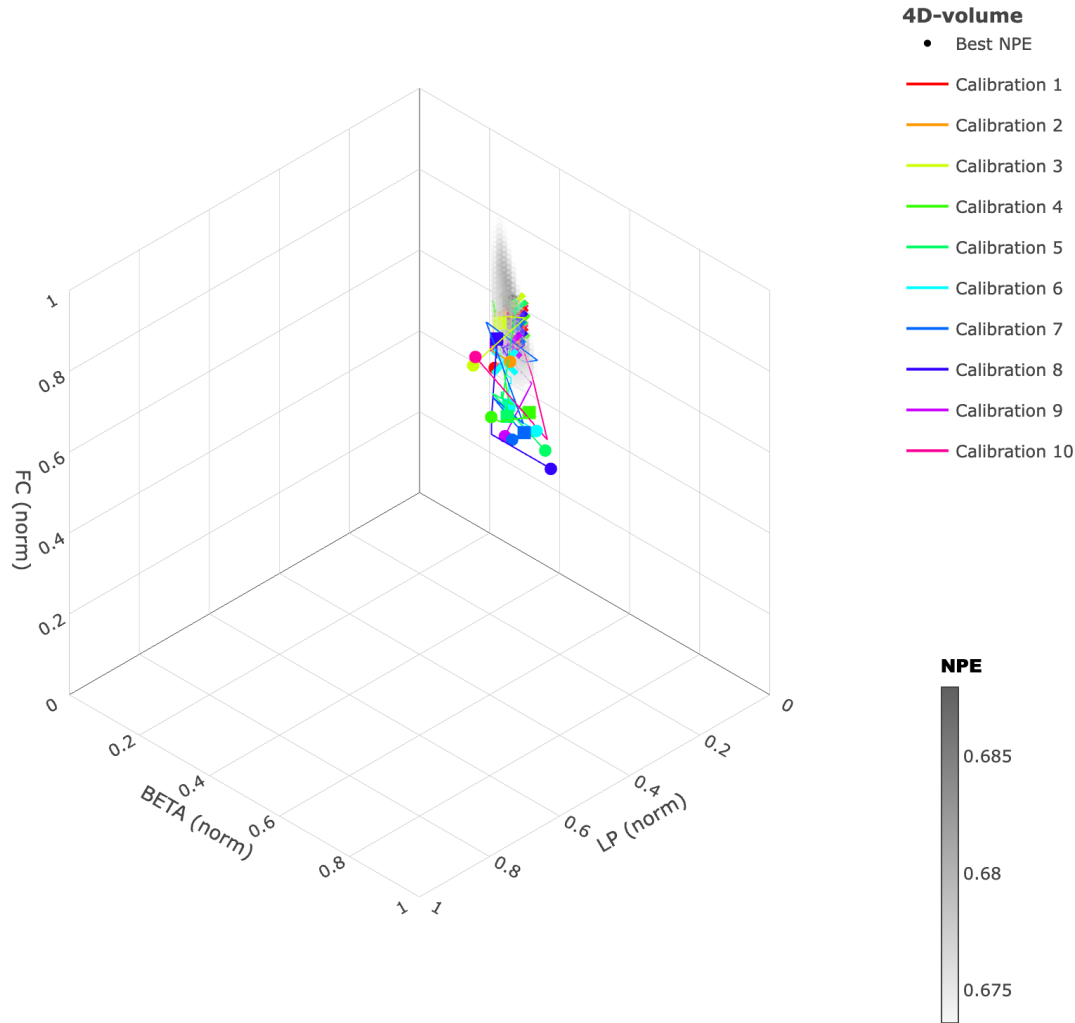
DEBB0132_4D_A: Persistence Diagram, top 5%



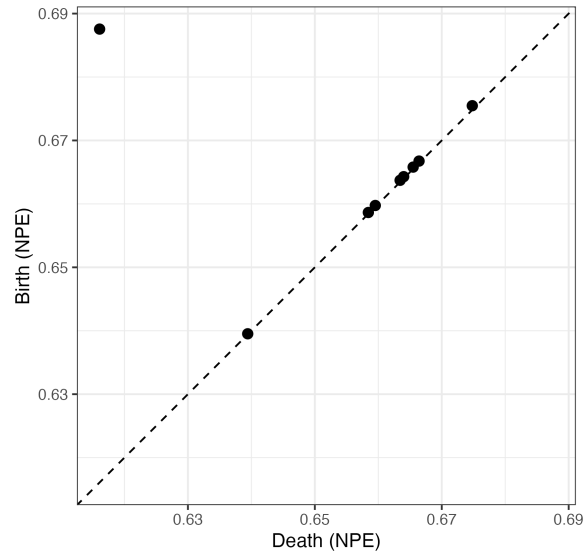
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.6847416	0.68597155	0.68629494	0.6864328	0.68661823
2	0.68231335	0.68487665	0.6858971	0.68660758	0.68661823
3	0.67418559	0.67897744	0.68122065	0.68252068	0.68661823
4	0.68298313	0.68654579	0.68664662	0.68665052	0.68661823
5	0.6797434	0.68280572	0.68280572	0.68556788	0.68661823
6	0.66001007	0.66740493	0.66820728	0.66895607	0.68661823
7	0.67388635	0.68014065	0.68096051	0.68176826	0.68661823
8	0.66603546	0.66767776	0.66855574	0.68490337	0.68661823
9	0.68373332	0.68385795	0.68575596	0.68644773	0.68661823
10	0.67955672	0.68416824	0.68469792	0.68515804	0.68661823

DEBB0132_4D_B, BETA_LP_FC_SFCF

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



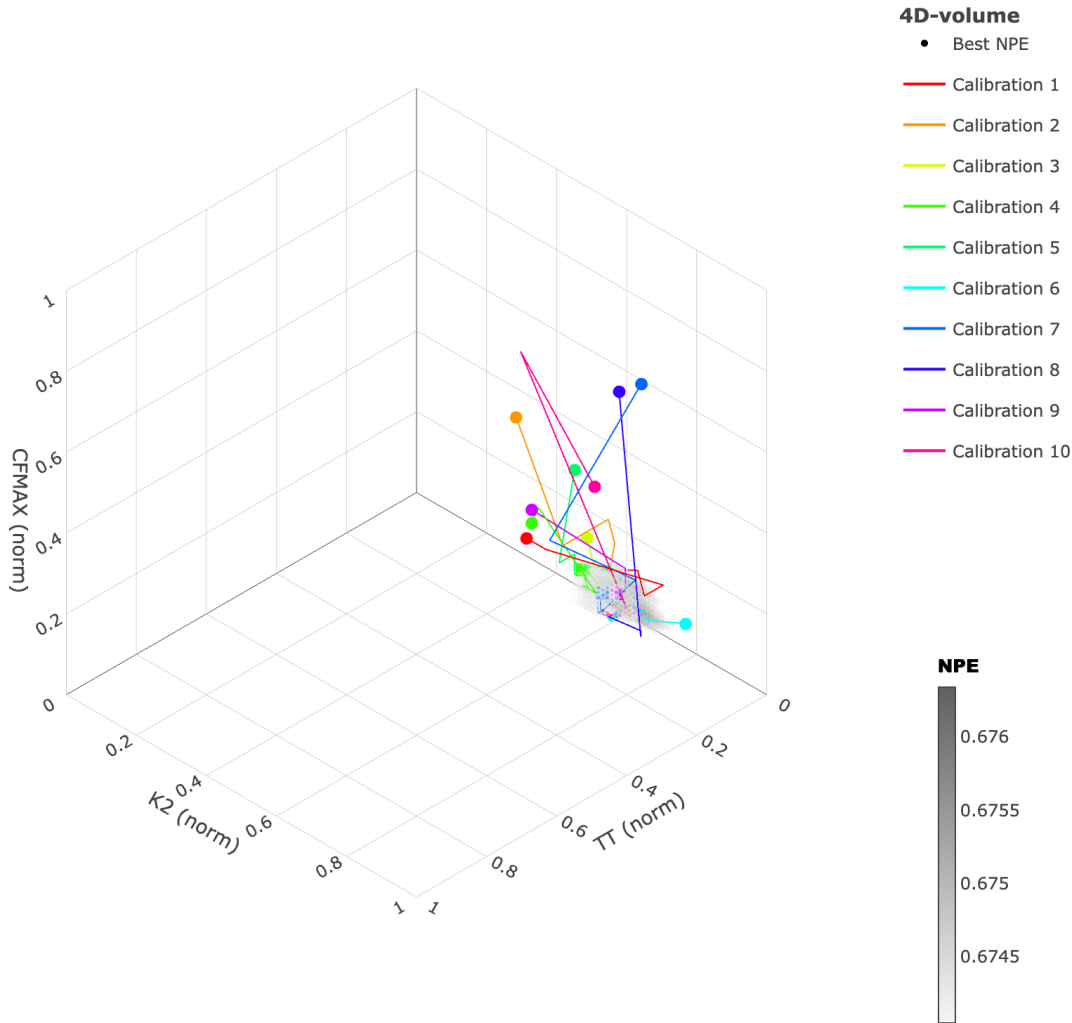
DEBB0132_4D_B: Persistence Diagram, top 5%



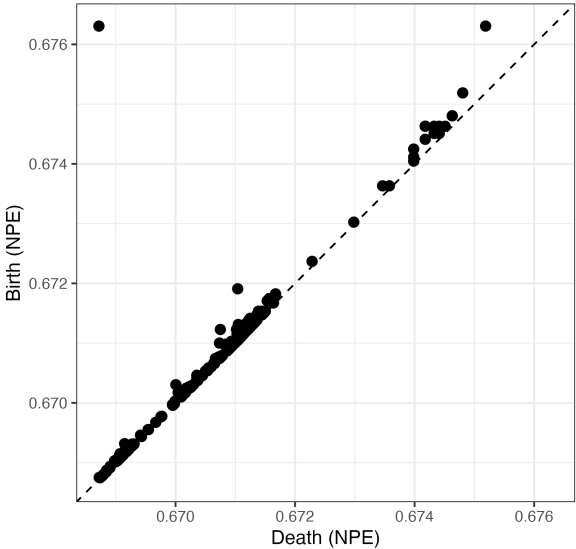
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.68250586	0.68287181	0.68371623	0.68637354	0.68794485
2	0.67817602	0.68473759	0.68586611	0.68719714	0.68794485
3	0.67755906	0.67984717	0.68676922	0.68748111	0.68794485
4	0.66549113	0.68422439	0.68541327	0.68602156	0.68794485
5	0.66418439	0.66564759	0.68505833	0.6869271	0.68794485
6	0.66803151	0.67402652	0.67575327	0.67625766	0.68794485
7	0.66209963	0.67876971	0.68299026	0.6841435	0.68794485
8	0.67418267	0.67766068	0.67842653	0.68535658	0.68794485
9	0.67444265	0.67731344	0.67926437	0.68032145	0.68794485
10	0.68425217	0.68442608	0.68601266	0.68702009	0.68794485

DEBB0132_4D_D, K2_TT_CFMAX_PERC

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



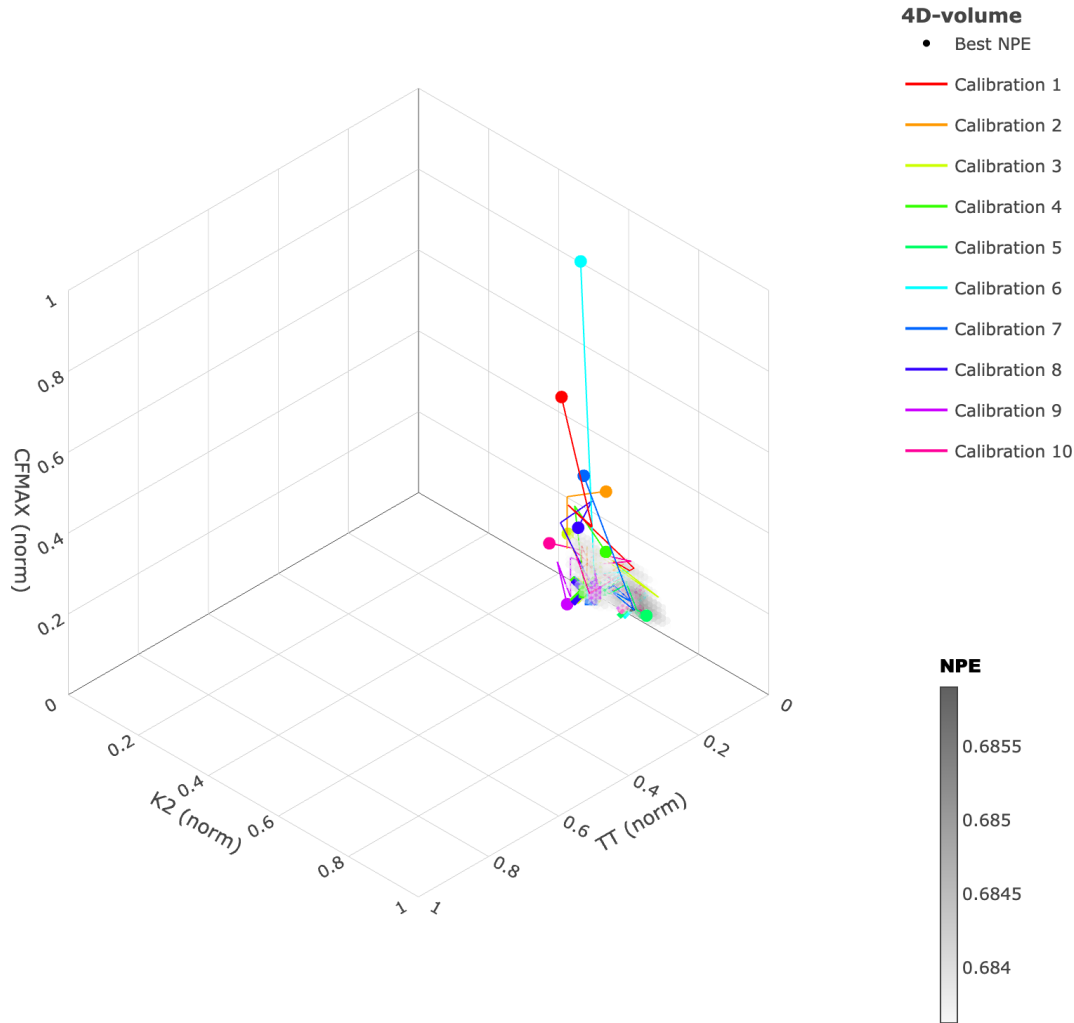
DEBB0132_4D_D: Persistence Diagram, top 5%



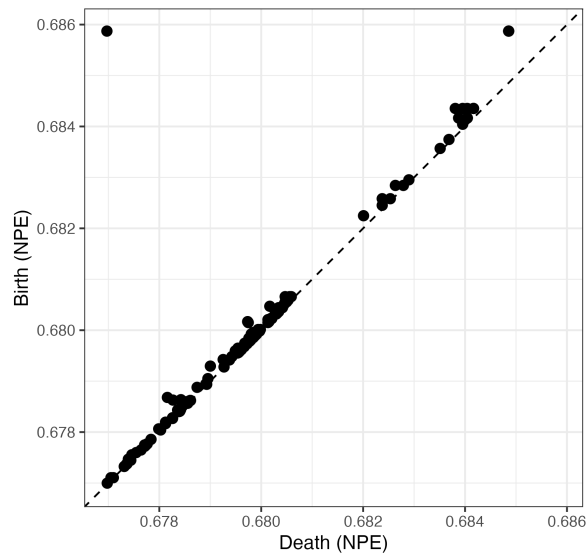
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.67550906	0.67610706	0.67619171	0.67625031	0.6763375
2	0.67465511	0.67627277	0.6762728	0.67628466	0.6763375
3	0.67549169	0.67566322	0.6760433	0.67632403	0.6763375
4	0.67458181	0.67468168	0.67474401	0.67613894	0.6763375
5	0.67457692	0.67558555	0.67609127	0.67613306	0.6763375
6	0.67610969	0.67613185	0.67617625	0.67619463	0.6763375
7	0.67463232	0.67496354	0.67496354	0.67549363	0.6763375
8	0.67547843	0.67609345	0.67617683	0.67620705	0.6763375
9	0.67476916	0.67601702	0.67604503	0.67604533	0.6763375
10	0.67615551	0.6761832	0.67618528	0.67621442	0.6763375

DEBB0132_4D_E, K2_TT_CFMAX_PERC

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



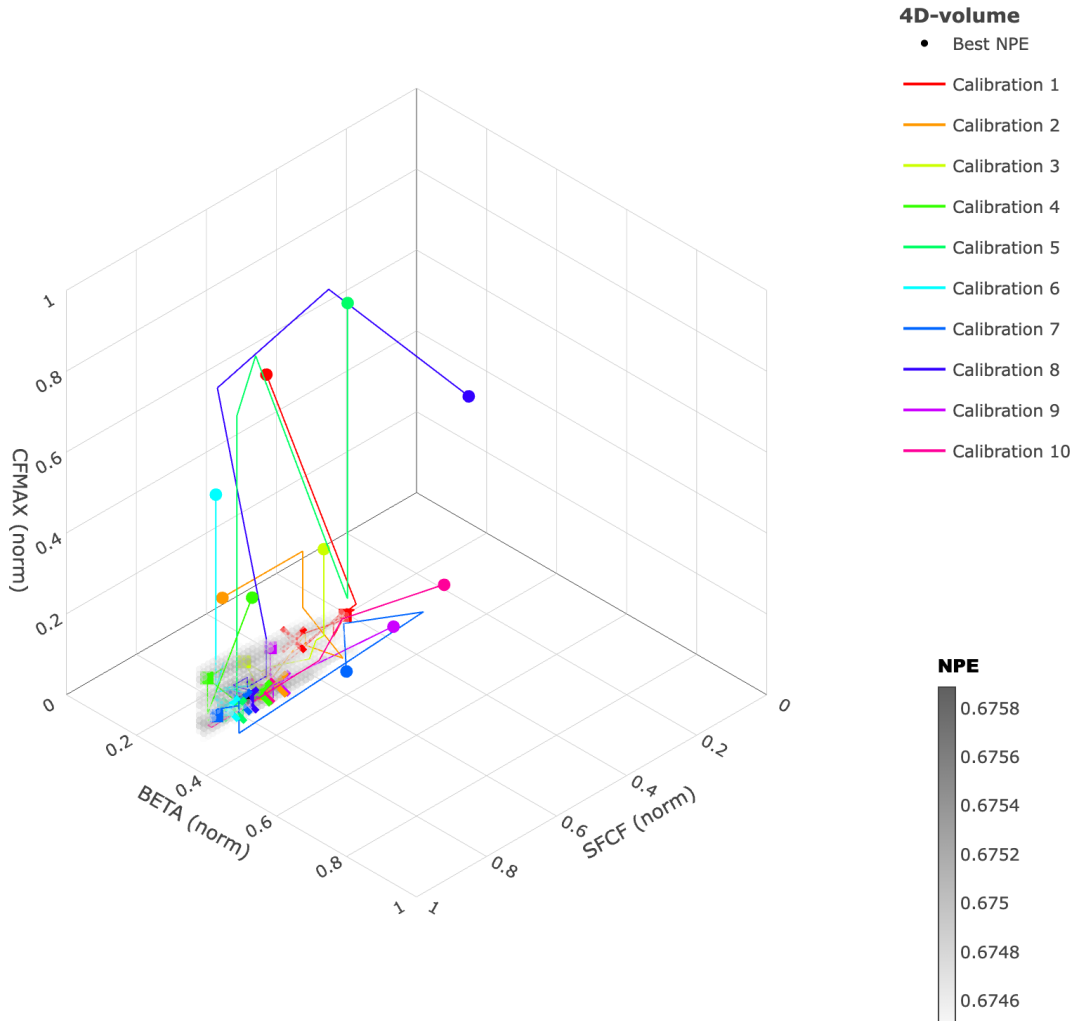
DEBB0132_4D_E: Persistence Diagram, top 5%



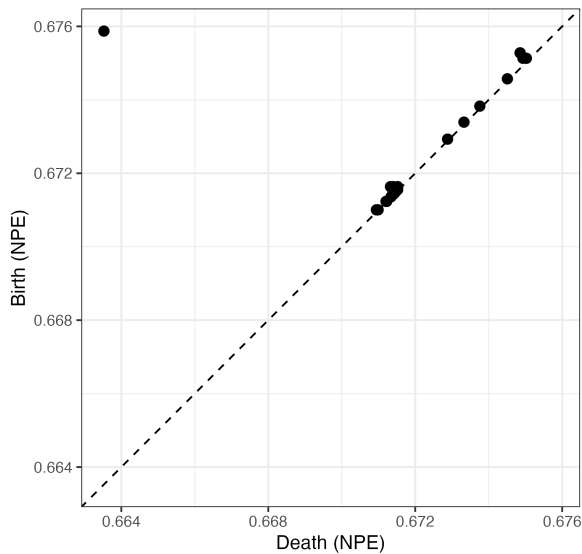
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.68450083	0.685664	0.68585996	0.68586593	0.68589792
2	0.68462213	0.68464563	0.68464751	0.68466284	0.68589792
3	0.6842164	0.68450437	0.68464017	0.68465663	0.68589792
4	0.68463492	0.68466286	0.68466286	0.68467867	0.68589792
5	0.6842804	0.68490087	0.68588304	0.68591289	0.68589792
6	0.68450846	0.6846246	0.68465403	0.6858762	0.68589792
7	0.68449049	0.6845584	0.68465993	0.68466258	0.68589792
8	0.68424959	0.68462624	0.68462636	0.68466876	0.68589792
9	0.68440169	0.68458716	0.68578302	0.68606027	0.68589792
10	0.68576979	0.68579394	0.68597989	0.68600147	0.68589792

DEBB0132_4D_J, BETA_SFCE_CFMAX_Alpha

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



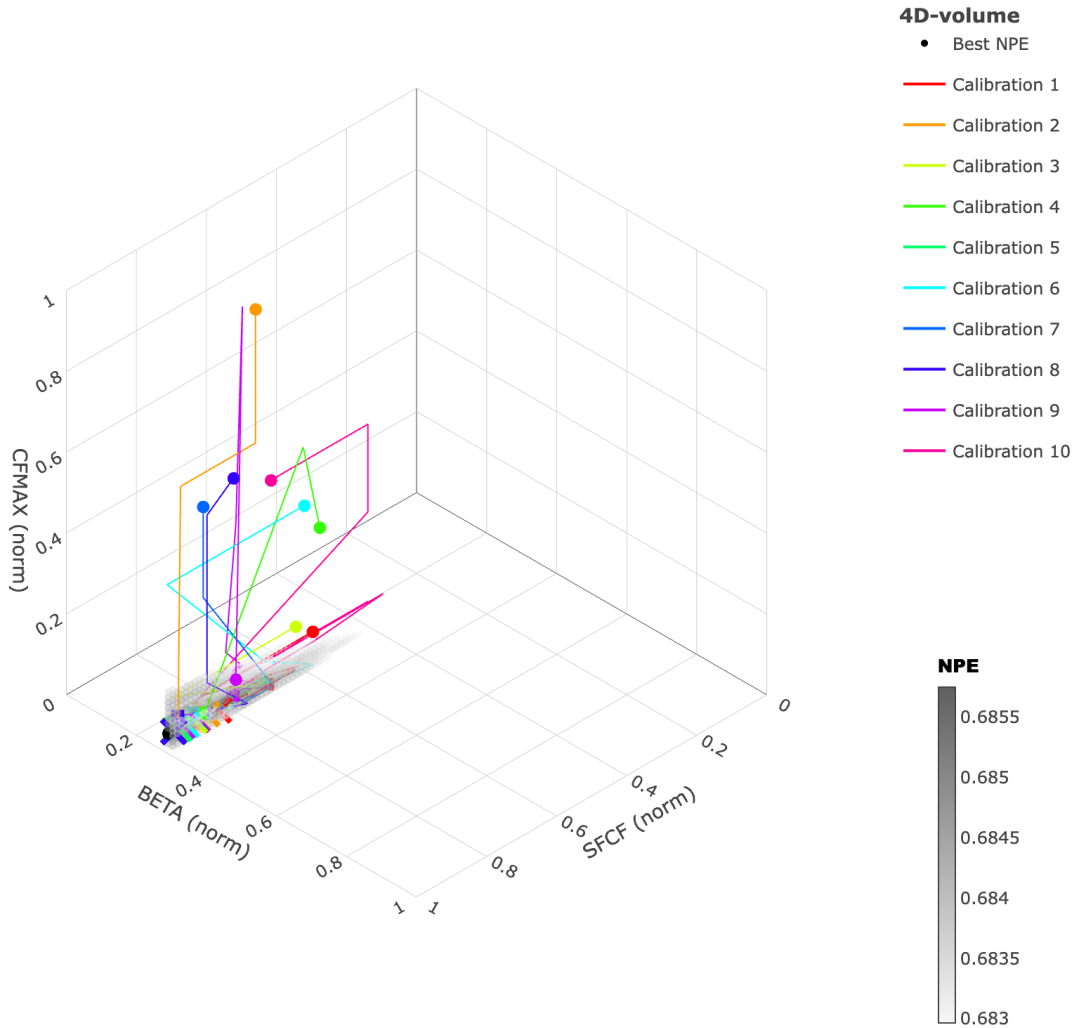
DEBB0132_4D_J: Persistence Diagram, top 5%



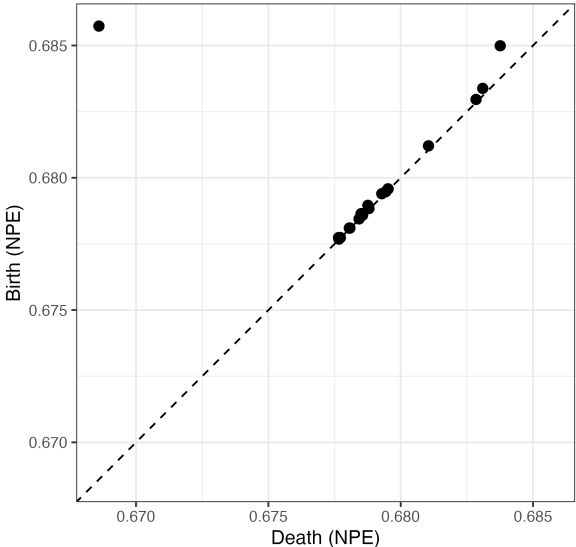
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.67429102	0.67485289	0.67500873	0.67518629	0.67588568
2	0.67560354	0.67573516	0.67575588	0.67576395	0.67588568
3	0.67538054	0.67575921	0.67582152	0.67585753	0.67588568
4	0.67529878	0.6757331	0.67573529	0.67585211	0.67588568
5	0.67568552	0.67569576	0.67569765	0.67570084	0.67588568
6	0.67558214	0.67573797	0.67573888	0.67584633	0.67588568
7	0.67453908	0.67484257	0.67562233	0.67584974	0.67588568
8	0.67587375	0.67587677	0.67587919	0.67590371	0.67588568
9	0.67528065	0.67560717	0.67578866	0.67579291	0.67588568
10	0.67577832	0.67578043	0.67585692	0.6758607	0.67588568

DEBB0132_4D_K, BETA_SFCE_CFMAX_Alpha

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



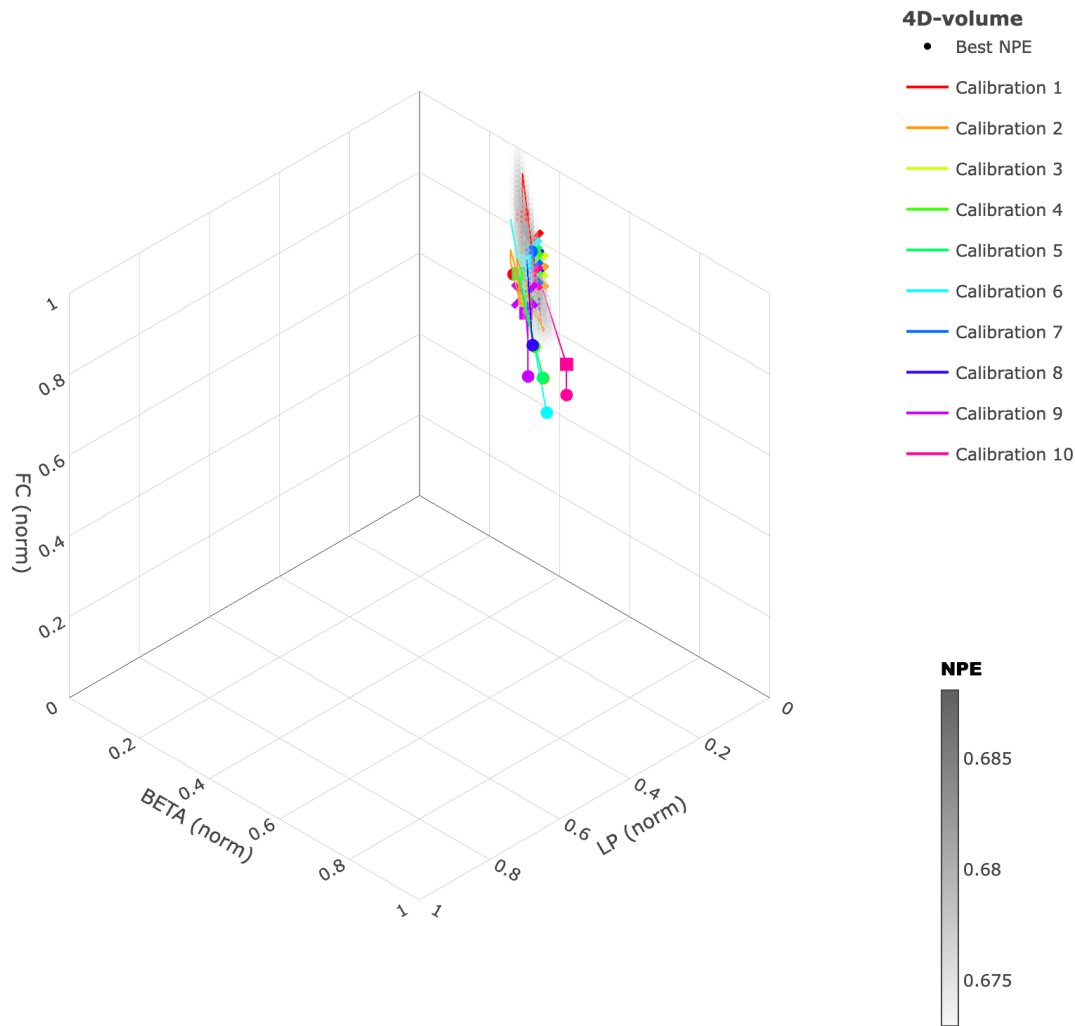
DEBB0132_4D_K: Persistence Diagram, top 5%



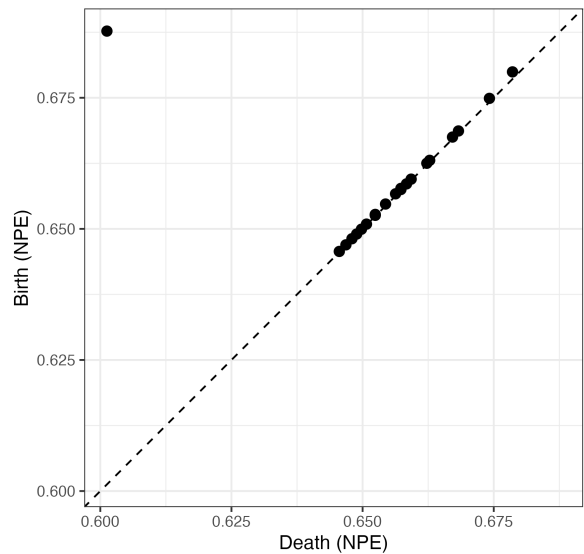
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.6843184	0.68487995	0.6853663	0.68539286	0.68574733
2	0.68553754	0.68565169	0.68565331	0.68575119	0.68574733
3	0.68544107	0.68548731	0.68554196	0.68579933	0.68574733
4	0.68494802	0.6856518	0.6858112	0.68588228	0.68574733
5	0.6852283	0.68572116	0.68572651	0.68591858	0.68574733
6	0.68522807	0.68569889	0.68572575	0.68592286	0.68574733
7	0.68558628	0.6857597	0.68577179	0.68583677	0.68574733
8	0.68488634	0.68573585	0.68573585	0.68585185	0.68574733
9	0.68503345	0.68587821	0.68595279	0.6859533	0.68574733
10	0.68538297	0.68560047	0.68577091	0.68577195	0.68574733

DEBB0136_4D_A, BETA_LP_FC_SFCF

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



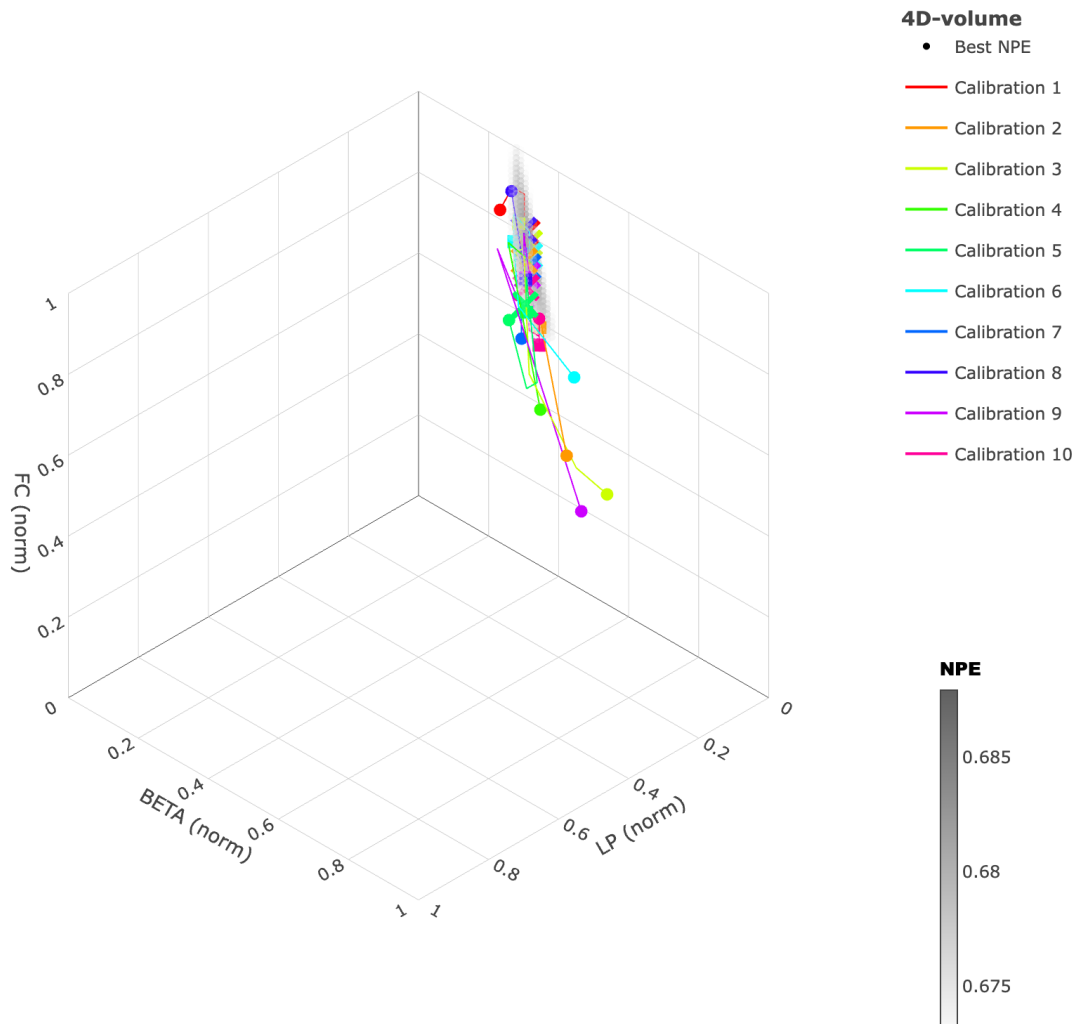
DEBB0136_4D_A: Persistence Diagram, top 5%



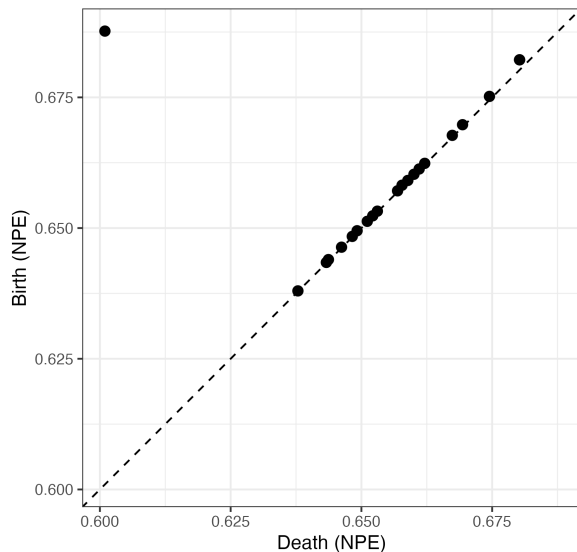
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.68435866	0.68792943	0.68795795	0.68796011	0.68805874
2	0.67616793	0.67675745	0.67677488	0.68562904	0.68805874
3	0.68323796	0.68373486	0.68382231	0.6857774	0.68805874
4	0.67698327	0.67712309	0.67719379	0.68493907	0.68805874
5	0.67535716	0.68439914	0.68481091	0.6854459	0.68805874
6	0.68114243	0.68141953	0.68149579	0.68645152	0.68805874
7	0.68072111	0.683327	0.68364316	0.68377392	0.68805874
8	0.68445657	0.68445657	0.68447381	0.68559275	0.68805874
9	0.67479829	0.67624772	0.67638114	0.6769975	0.68805874
10	0.66309373	0.68124257	0.68243969	0.68276762	0.68805874

DEBB0136_4D_B, BETA_LP_FC_SFCF

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



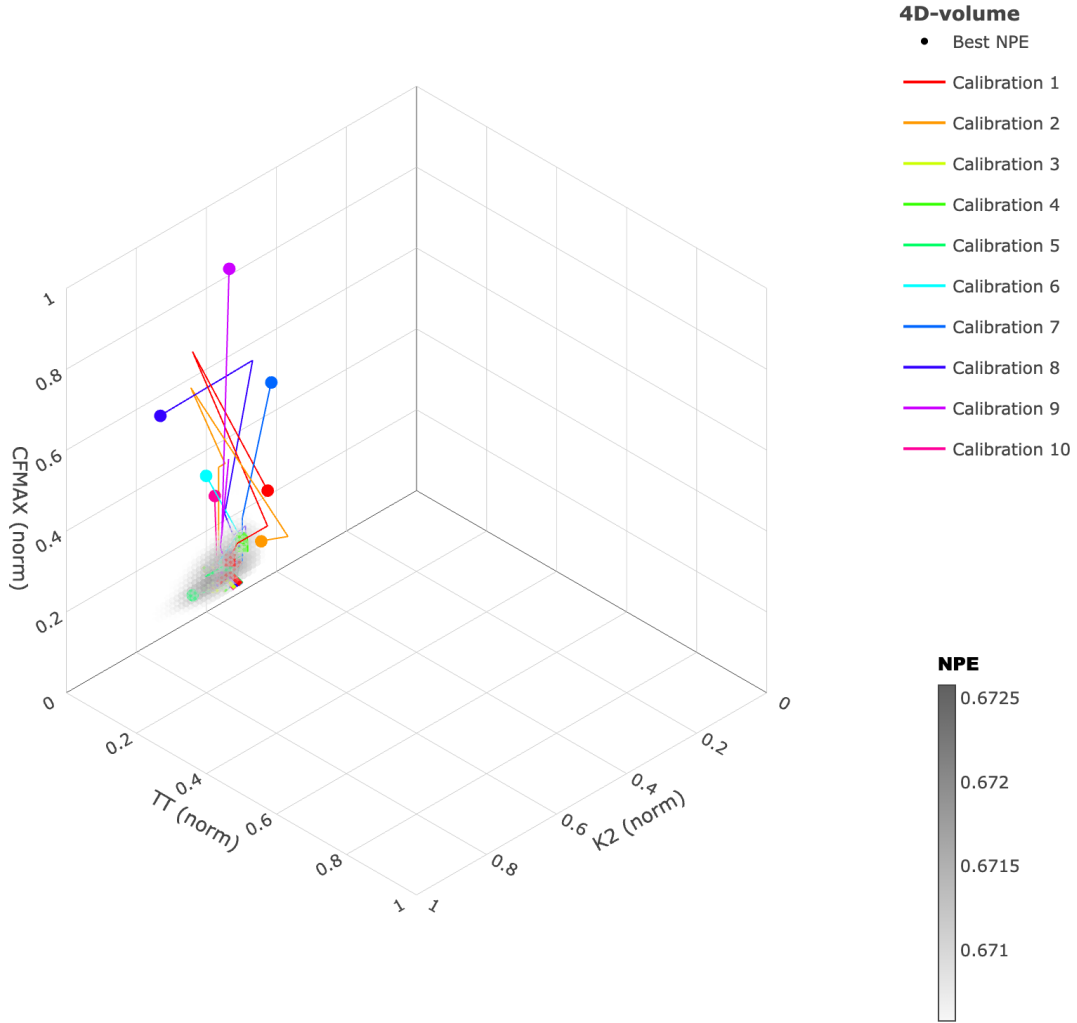
DEBB0136_4D_B: Persistence Diagram, top 5%



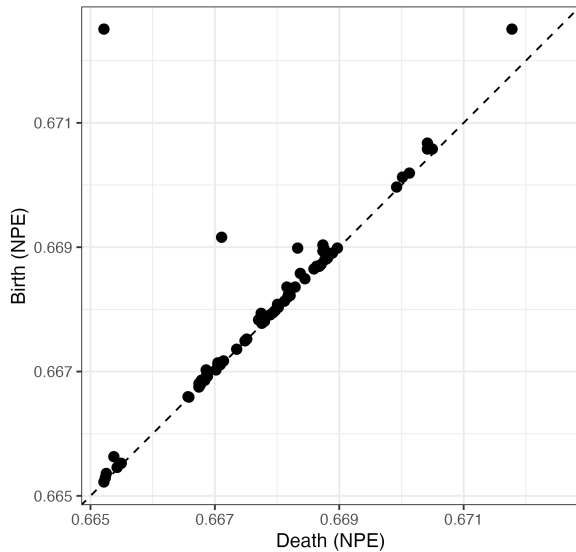
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.68392917	0.68756679	0.68760528	0.68770361	0.68790912
2	0.67363332	0.68044503	0.68167264	0.68273406	0.68790912
3	0.68217482	0.68694437	0.68732561	0.68773029	0.68790912
4	0.68390107	0.68414052	0.6848307	0.68551969	0.68790912
5	0.67247308	0.67421874	0.67451636	0.67455841	0.68790912
6	0.67479919	0.68573455	0.68643795	0.68647619	0.68790912
7	0.68138109	0.68308697	0.68375079	0.684006	0.68790912
8	0.67858046	0.67866675	0.67871657	0.68582799	0.68790912
9	0.67972365	0.67995324	0.68198341	0.68287703	0.68790912
10	0.67242746	0.67756449	0.67770873	0.67867367	0.68790912

DEBB0136_4D_D, TT_K2_CFMAX_PERC

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



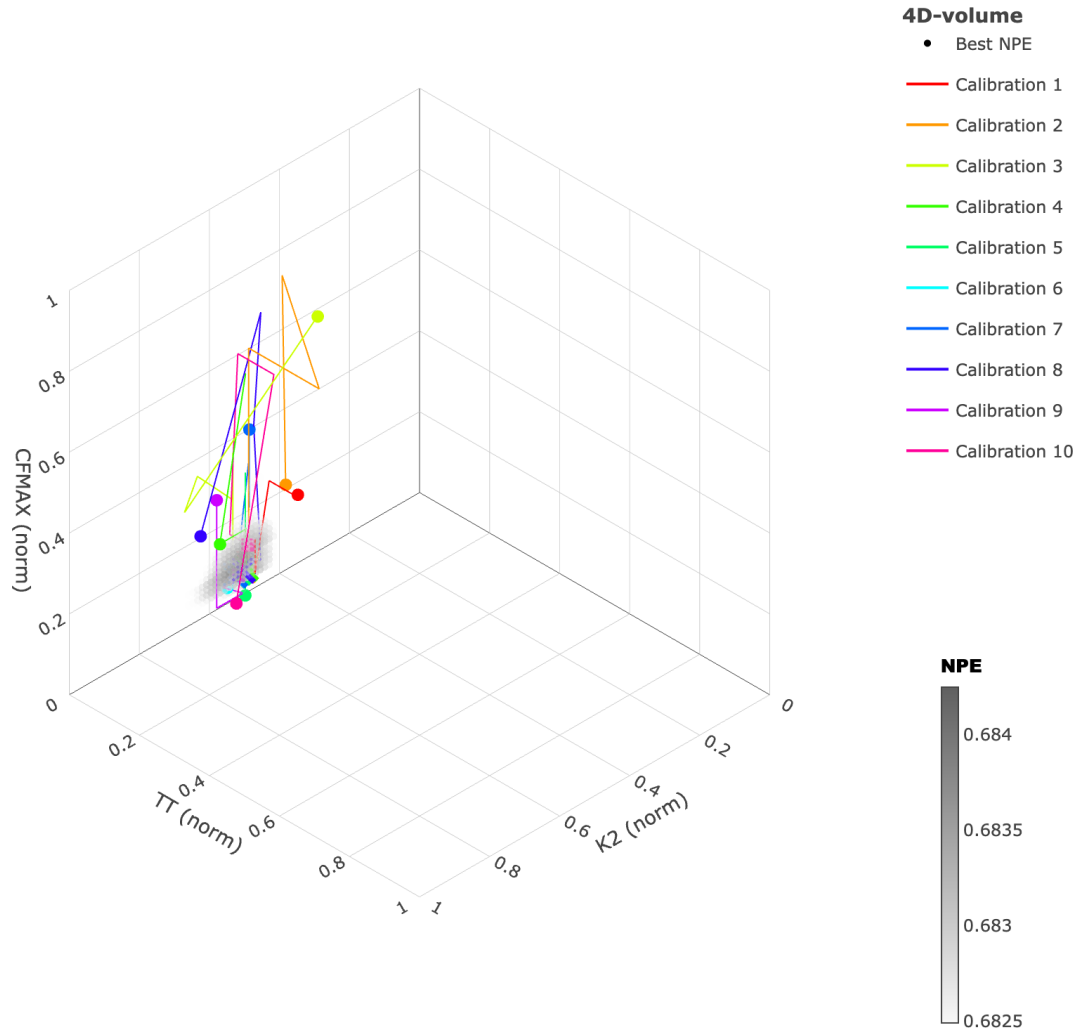
DEBB0136_4D_D: Persistence Diagram, top 5%



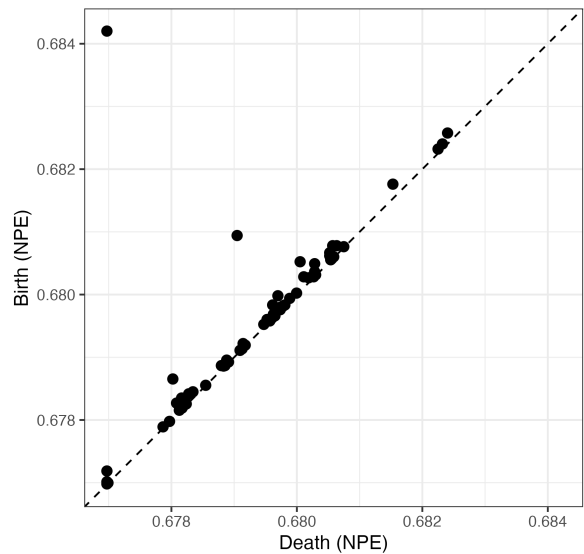
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.6720454	0.67245406	0.67255613	0.67257126	0.67257488
2	0.6724011	0.672524	0.6725705	0.67263338	0.67257488
3	0.67248116	0.6726922	0.67269546	0.67270224	0.67257488
4	0.67176192	0.67256506	0.67261014	0.67263264	0.67257488
5	0.67202326	0.67222333	0.67228189	0.67261489	0.67257488
6	0.67223463	0.67239719	0.67240238	0.67266111	0.67257488
7	0.67218242	0.67255389	0.6725681	0.67263319	0.67257488
8	0.67188592	0.67255973	0.67259067	0.67260215	0.67257488
9	0.67253556	0.6725947	0.67260604	0.67260604	0.67257488
10	0.67254364	0.67270091	0.67270091	0.6727168	0.67257488

DEBB0136_4D_E, TT_K2_CFMAX_PERC

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



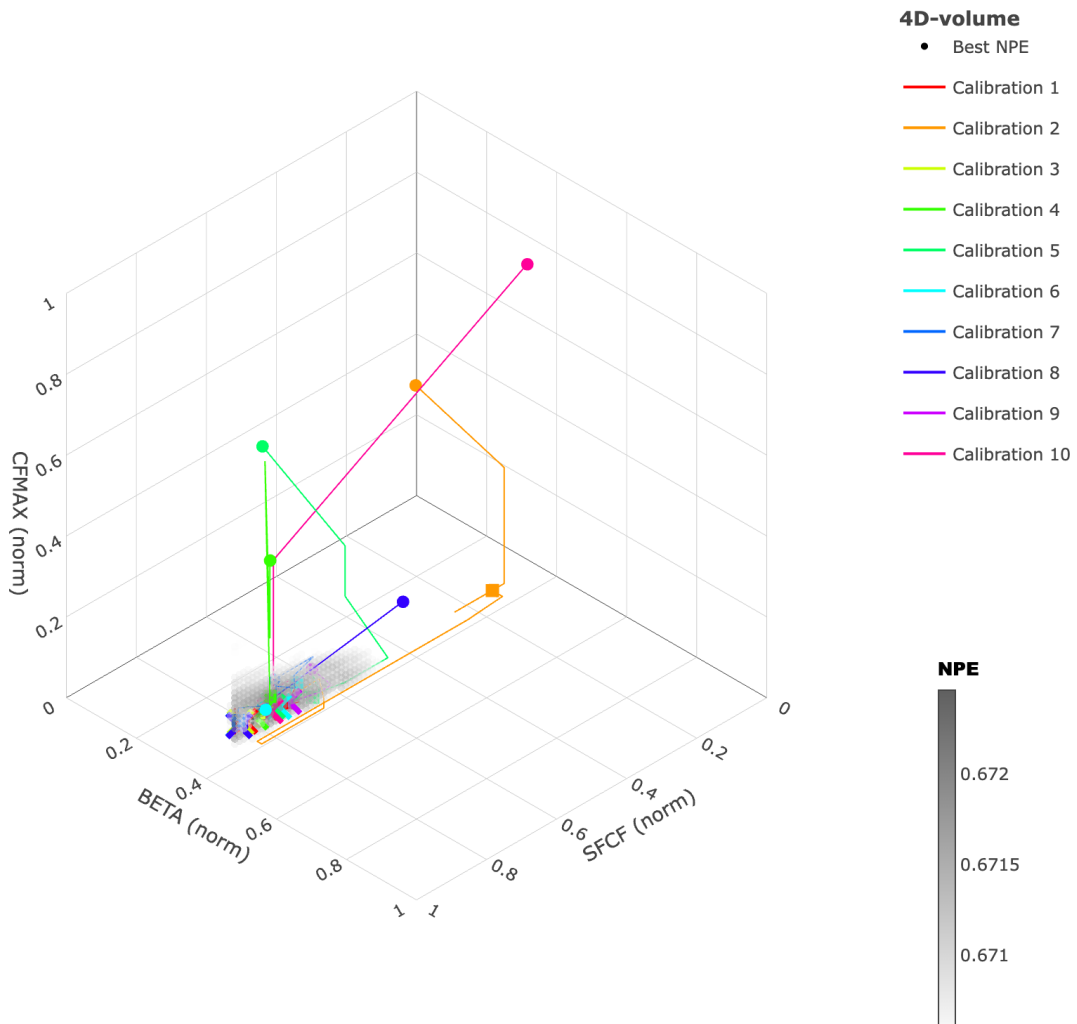
DEBB0136_4D_E: Persistence Diagram, top 5%



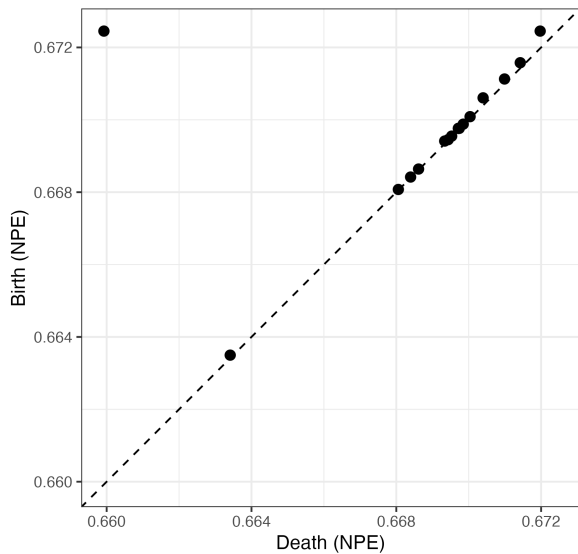
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.68414177	0.68442747	0.68450617	0.68454622	0.684249
2	0.68433993	0.68434204	0.68434263	0.68434852	0.684249
3	0.68428862	0.68454813	0.68455264	0.68457193	0.684249
4	0.68438611	0.68440976	0.68441053	0.68441352	0.684249
5	0.68443058	0.68453176	0.68454442	0.6845527	0.684249
6	0.68420763	0.68453953	0.68453953	0.68457531	0.684249
7	0.6844424	0.68449893	0.68452993	0.68456021	0.684249
8	0.68431627	0.6843397	0.68434103	0.68440782	0.684249
9	0.68424188	0.68446915	0.68447205	0.68447259	0.684249
10	0.68365297	0.68376082	0.68393458	0.68447186	0.684249

DEBB0136_4D_J, BETA_SFCE_CFMAX_Alpha

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



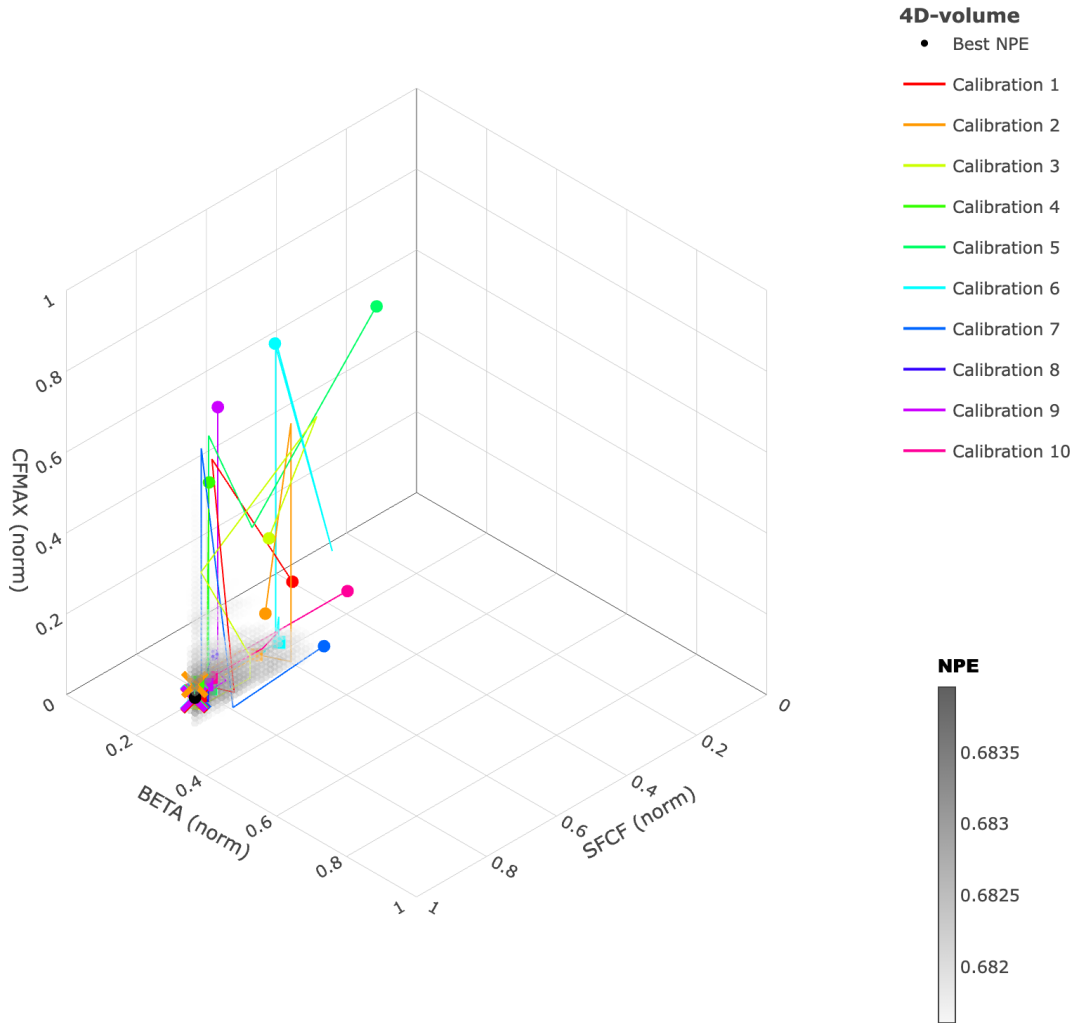
DEBB0136_4D_J: Persistence Diagram, top 5%



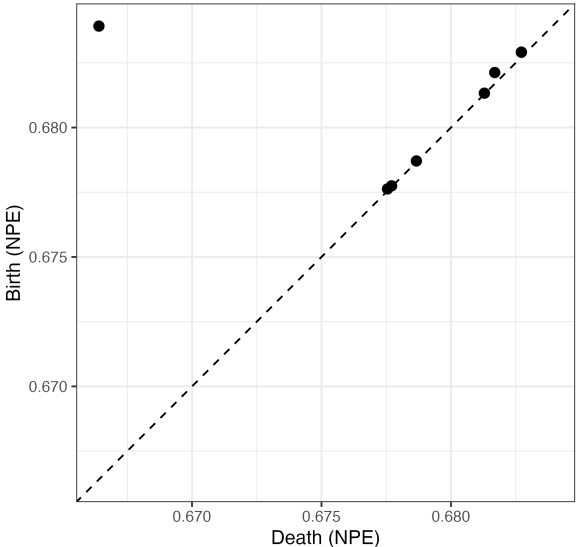
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.67224389	0.67234397	0.67237686	0.67245876	0.67246127
2	0.66134619	0.67240154	0.67241078	0.67247929	0.67246127
3	0.6722501	0.67231657	0.67247622	0.67247753	0.67246127
4	0.67233753	0.67244162	0.67244738	0.67245882	0.67246127
5	0.67158088	0.67182481	0.6720966	0.67237968	0.67246127
6	0.67196961	0.67201456	0.67202739	0.67238774	0.67246127
7	0.67239562	0.67242734	0.67244691	0.67248464	0.67246127
8	0.67243965	0.67246899	0.67247103	0.67247103	0.67246127
9	0.6721068	0.67221447	0.67221447	0.67229686	0.67246127
10	0.67171313	0.67244421	0.67244421	0.67244456	0.67246127

DEBB0136_4D_K, BETA_SFCE_CFMAX_Alpha

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



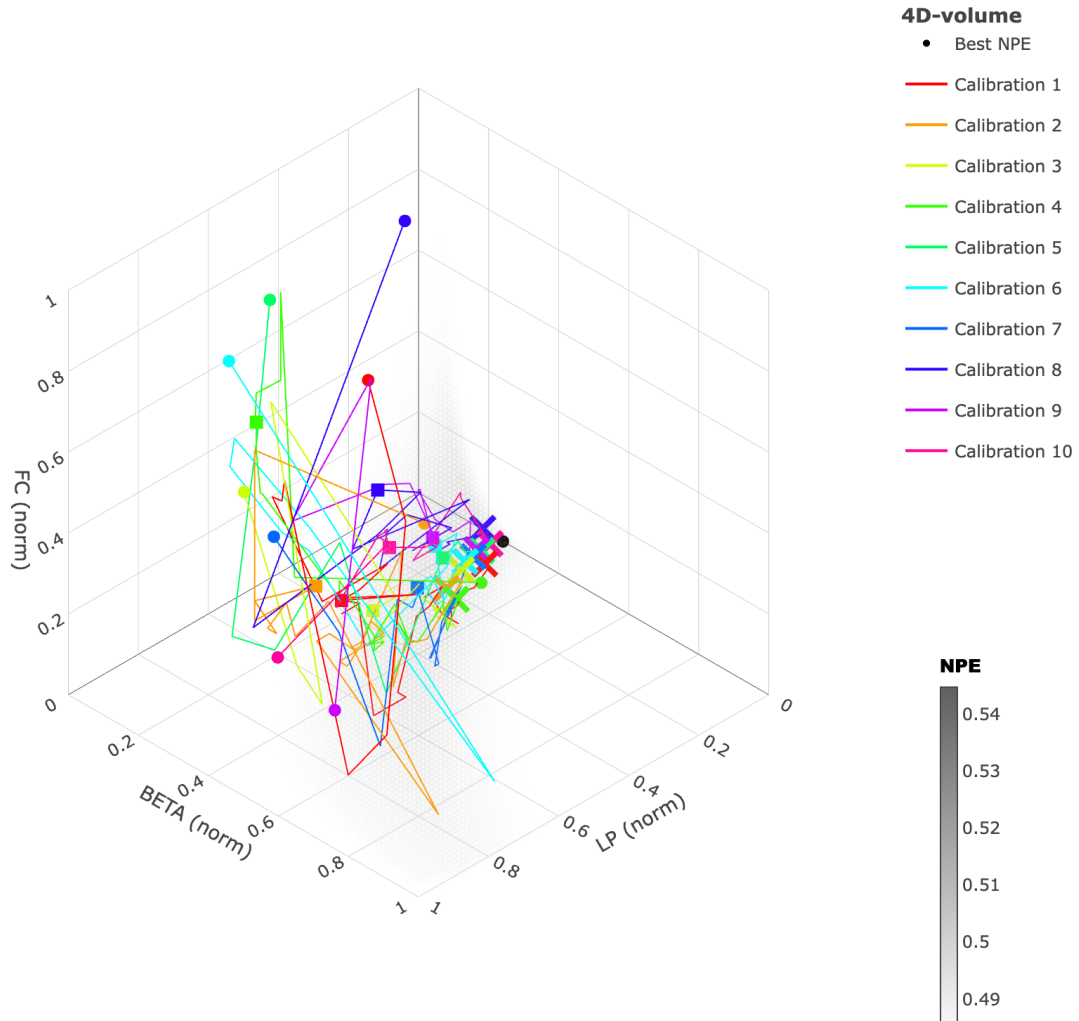
DEBB0136_4D_K: Persistence Diagram, top 5%



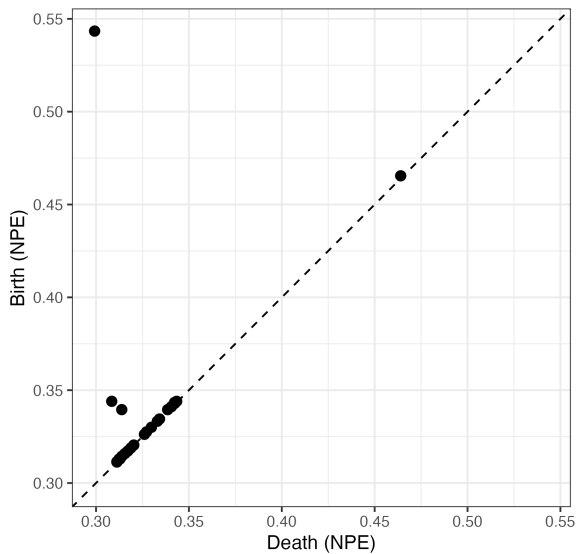
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.68396138	0.68405701	0.68405701	0.68415254	0.68395488
2	0.68252061	0.68388522	0.68389797	0.6841982	0.68395488
3	0.68405152	0.68419024	0.68420274	0.68420355	0.68395488
4	0.68408826	0.68418952	0.68418952	0.68419175	0.68395488
5	0.68386622	0.68393589	0.68419658	0.68419674	0.68395488
6	0.6820989	0.68237908	0.68414457	0.68419315	0.68395488
7	0.68406353	0.68412455	0.68412455	0.68416249	0.68395488
8	0.6838934	0.68407544	0.68407731	0.6841822	0.68395488
9	0.68324141	0.68419724	0.68420131	0.68420994	0.68395488
10	0.68395798	0.68403729	0.68418697	0.68418697	0.68395488

ES000356_4D_A, BETA_LP_FC_K2

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



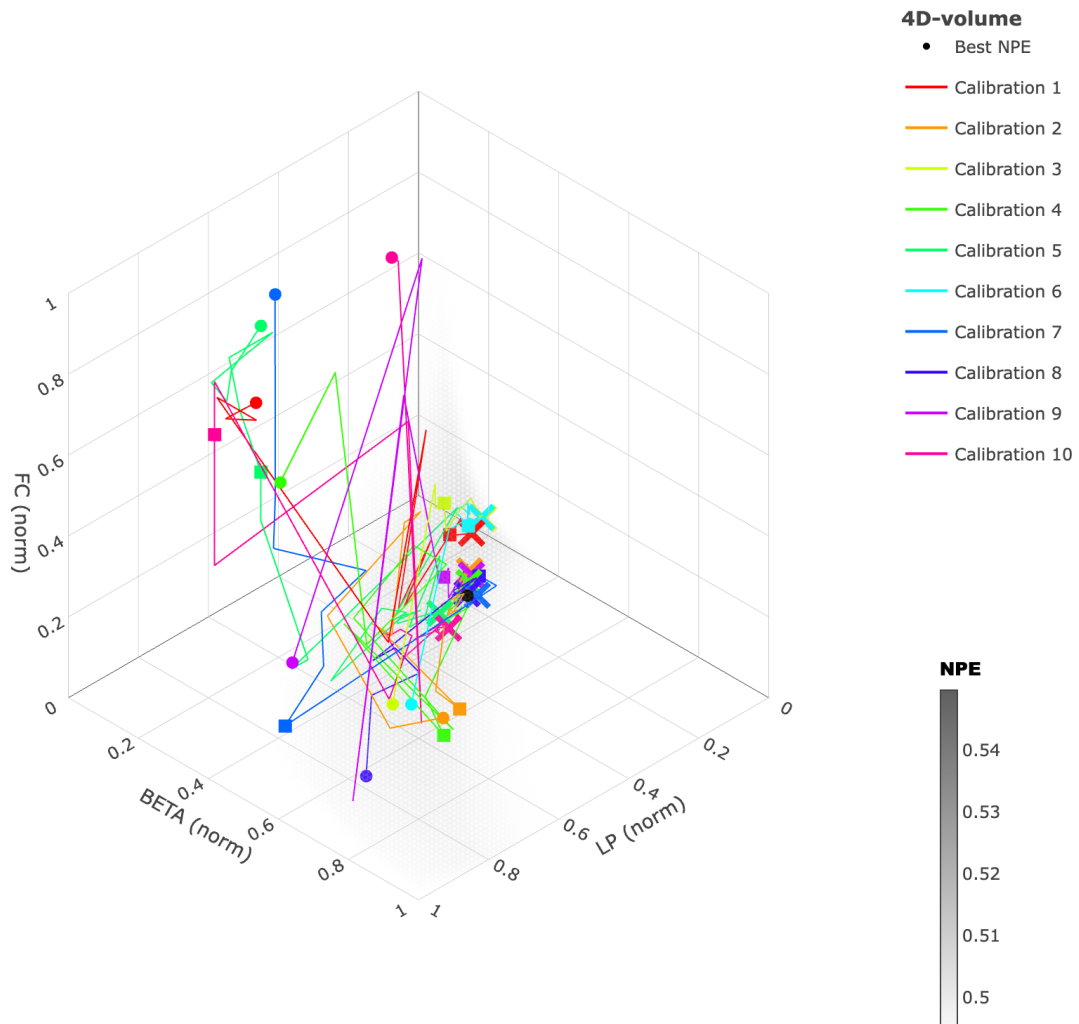
ES000356_4D_A: Persistence Diagram, top 5%



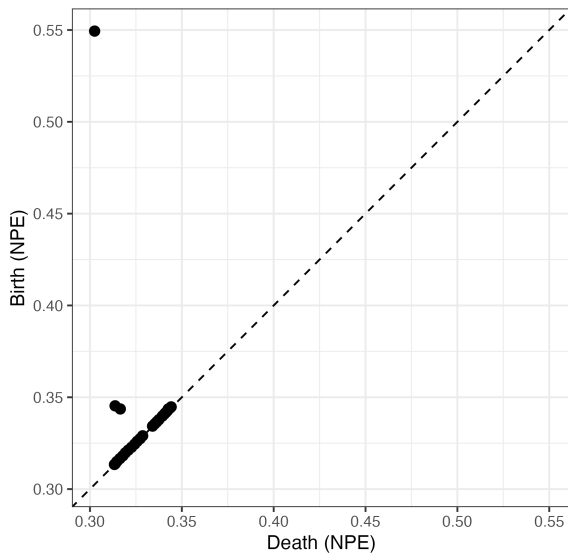
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.49530086	0.53816162	0.54640705	0.55006792	0.54466486
2	0.46607777	0.49046103	0.50873099	0.54289425	0.54466486
3	0.5028814	0.54159719	0.54259453	0.54674793	0.54466486
4	0.45306749	0.47271161	0.50407765	0.54459413	0.54466486
5	0.52272708	0.53809648	0.54697842	0.54922543	0.54466486
6	0.51442137	0.52853271	0.54547581	0.54638676	0.54466486
7	0.52849767	0.5364379	0.54410472	0.54774636	0.54466486
8	0.47515603	0.52888767	0.54217383	0.54800394	0.54466486
9	0.5063591	0.54279325	0.54789223	0.54816379	0.54466486
10	0.511446	0.54166023	0.54166023	0.54720758	0.54466486

ES000356_4D_B, BETA_LP_FC_K2

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



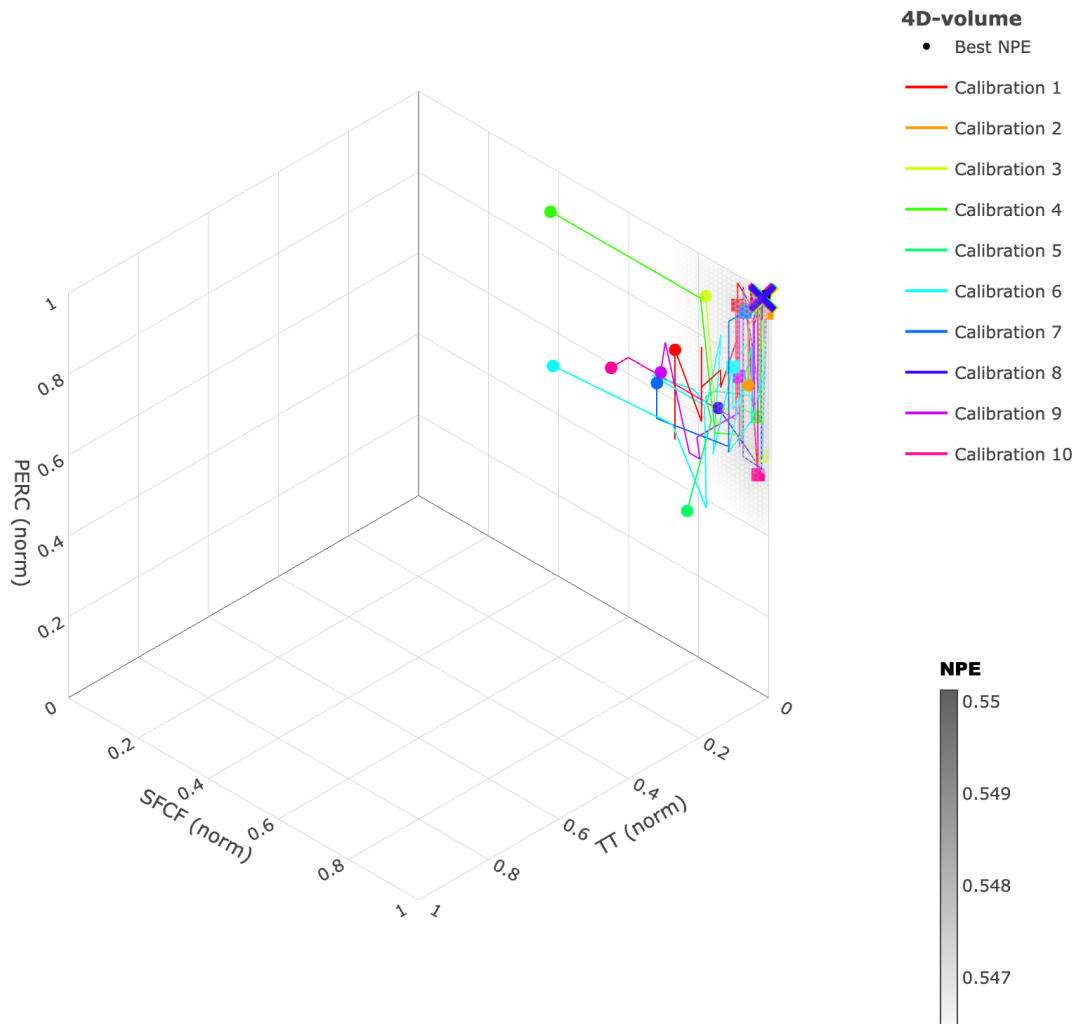
ES000356_4D_B: Persistence Diagram, top 5%



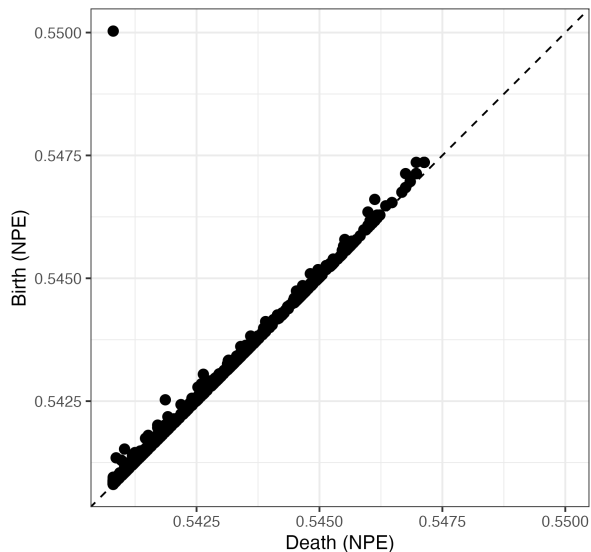
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.54758964	0.5478241	0.54821772	0.55024443	0.54964378
2	0.53342983	0.54298373	0.55133355	0.554617	0.54964378
3	0.54436062	0.54988051	0.55308582	0.55403744	0.54964378
4	0.52183512	0.52970724	0.55243924	0.55503097	0.54964378
5	0.46987895	0.5156913	0.53866971	0.55004674	0.54964378
6	0.51925642	0.54999099	0.55322291	0.55354101	0.54964378
7	0.4965088	0.52538131	0.52548662	0.55478655	0.54964378
8	0.54478835	0.55008481	0.55242761	0.55362367	0.54964378
9	0.54992238	0.55383995	0.55384063	0.5545031	0.54964378
10	0.43494778	0.52972766	0.54453571	0.55158082	0.54964378

ES000356_4D_D, SFCF_TT_PERC_CFMAX

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



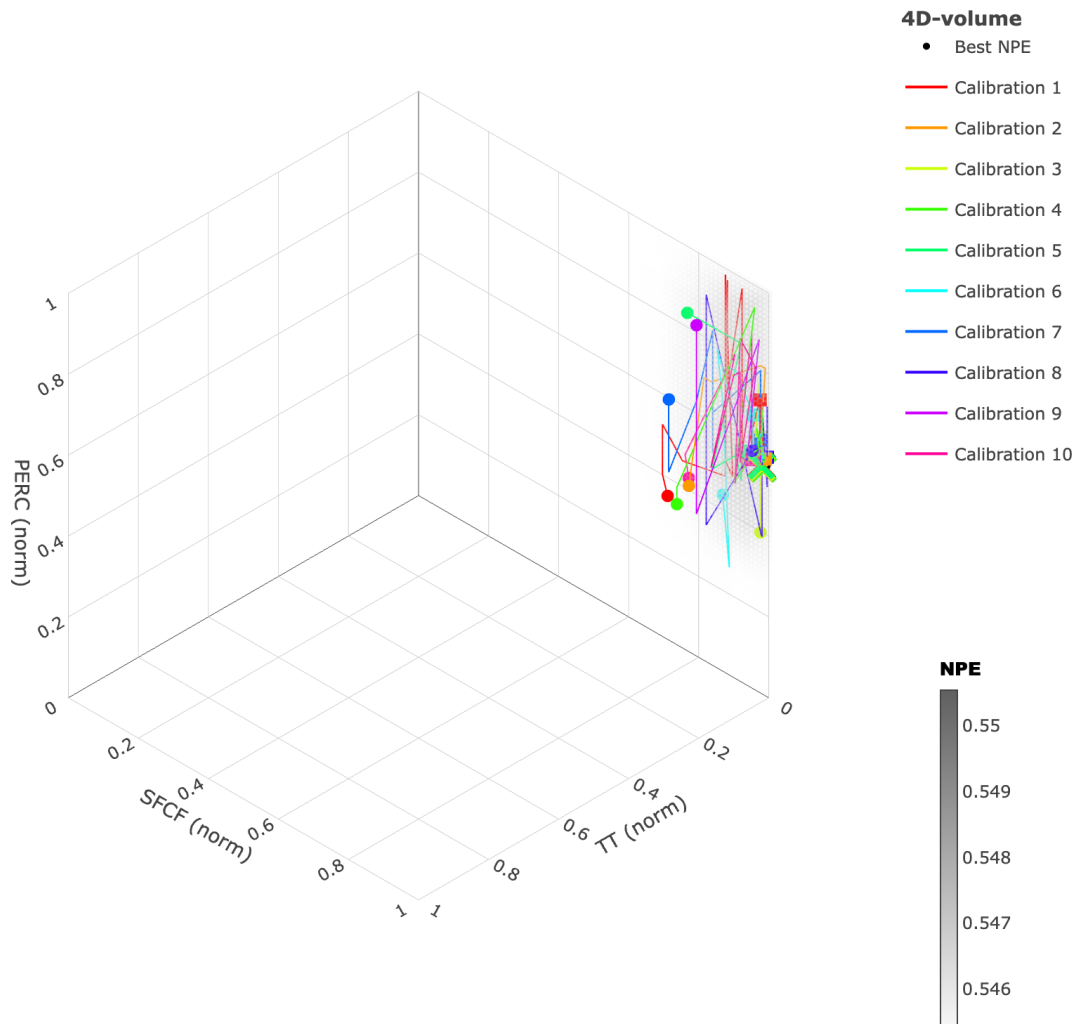
ES000356_4D_D: Persistence Diagram, top 5%



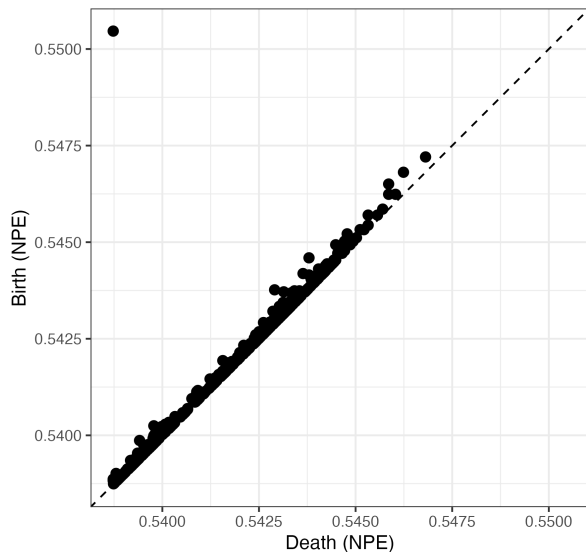
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.54866532	0.5499206	0.55006387	0.55014854	0.55012089
2	0.54947849	0.550138	0.55013903	0.55014055	0.55012089
3	0.54752147	0.54980243	0.54981818	0.5499187	0.55012089
4	0.54886234	0.54929055	0.54933109	0.54975295	0.55012089
5	0.54952852	0.54957821	0.54996063	0.55015809	0.55012089
6	0.54668515	0.54984866	0.55011686	0.55013716	0.55012089
7	0.54708702	0.54977828	0.55011514	0.55013722	0.55012089
8	0.54914429	0.54990018	0.54991548	0.55004235	0.55012089
9	0.54776671	0.54991659	0.55003672	0.55003672	0.55012089
10	0.54752886	0.54809926	0.54970388	0.55011059	0.55012089

ES000356_4D_E, SFCF_TT_PERC_CFMAX

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



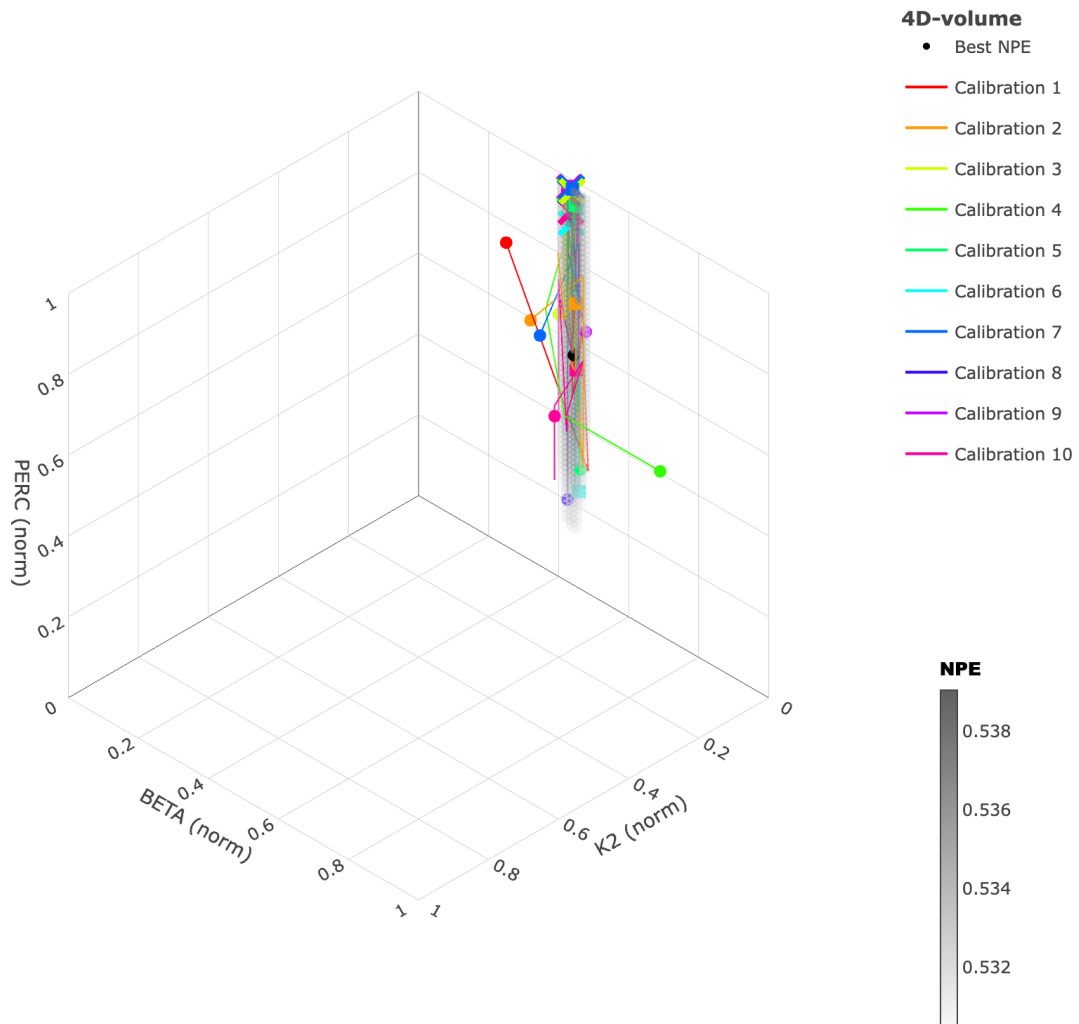
ES000356_4D_E: Persistence Diagram, top 5%



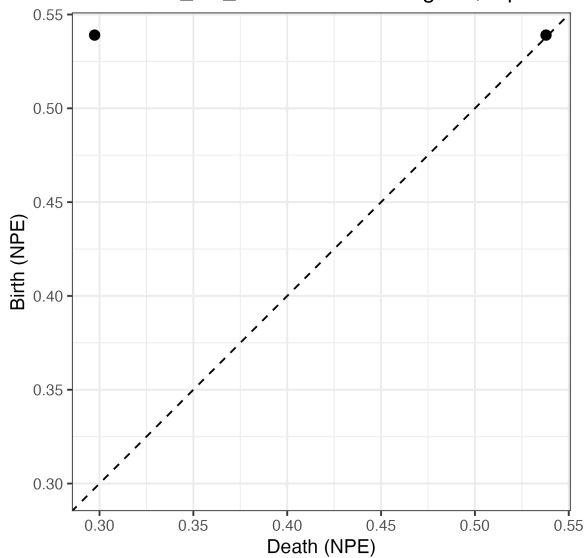
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.54916869	0.55032345	0.55033858	0.55056547	0.55053045
2	0.54868619	0.55005556	0.55029374	0.55042591	0.55053045
3	0.54978149	0.55026817	0.55035544	0.55058496	0.55053045
4	0.54789323	0.55004069	0.55010698	0.5505815	0.55053045
5	0.54957215	0.55040586	0.55042745	0.5505725	0.55053045
6	0.54979936	0.55050966	0.55056398	0.55057275	0.55053045
7	0.5491004	0.54926503	0.5494404	0.55038178	0.55053045
8	0.54986098	0.55020518	0.55020518	0.55043665	0.55053045
9	0.54747235	0.55048642	0.55053843	0.55056972	0.55053045
10	0.54992143	0.55017624	0.55018019	0.55018355	0.55053045

ES000356_4D_J, BETA_K2_PERC_MAXBAS

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



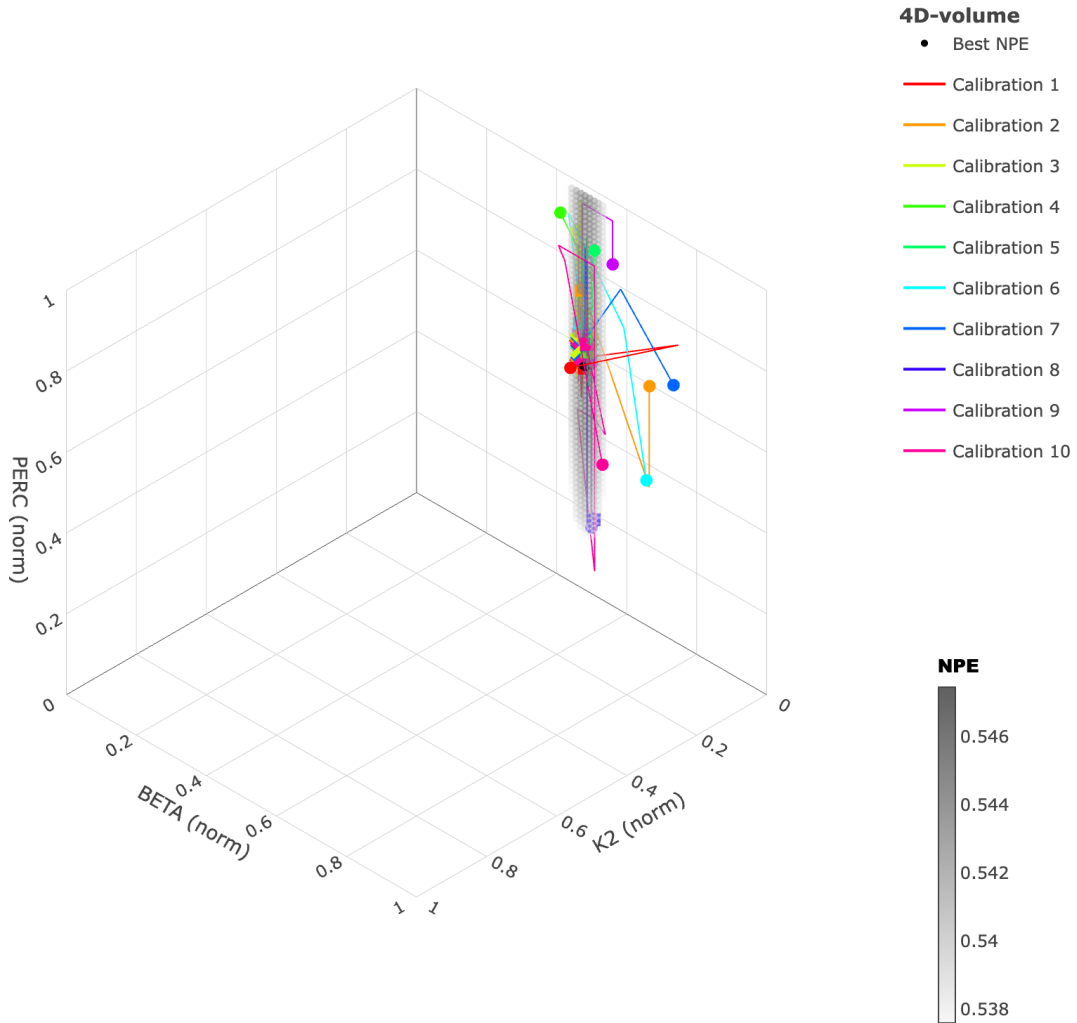
ES000356_4D_J: Persistence Diagram, top 5%



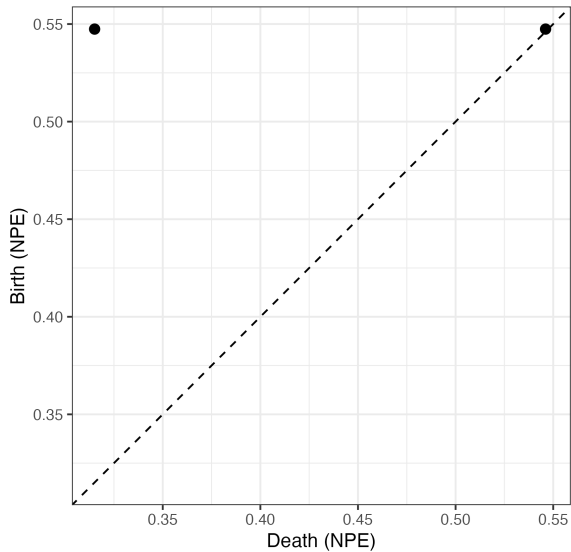
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.54341254	0.54393732	0.54393981	0.54483074	0.53904616
2	0.53100608	0.54252135	0.54467811	0.544903	0.53904616
3	0.53962546	0.53964185	0.53967902	0.54385134	0.53904616
4	0.52814074	0.5443873	0.5448572	0.5448782	0.53904616
5	0.54260827	0.54383132	0.54418792	0.54454109	0.53904616
6	0.51725536	0.54179272	0.54394754	0.54484625	0.53904616
7	0.54400891	0.54401421	0.5447972	0.54484439	0.53904616
8	0.54084906	0.54453604	0.5445564	0.54486056	0.53904616
9	0.54463234	0.5448361	0.5448451	0.54488124	0.53904616
10	0.53761362	0.54423364	0.54464558	0.54469658	0.53904616

ES000356_4D_K, BETA_K2_PERC_MAXBAS

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



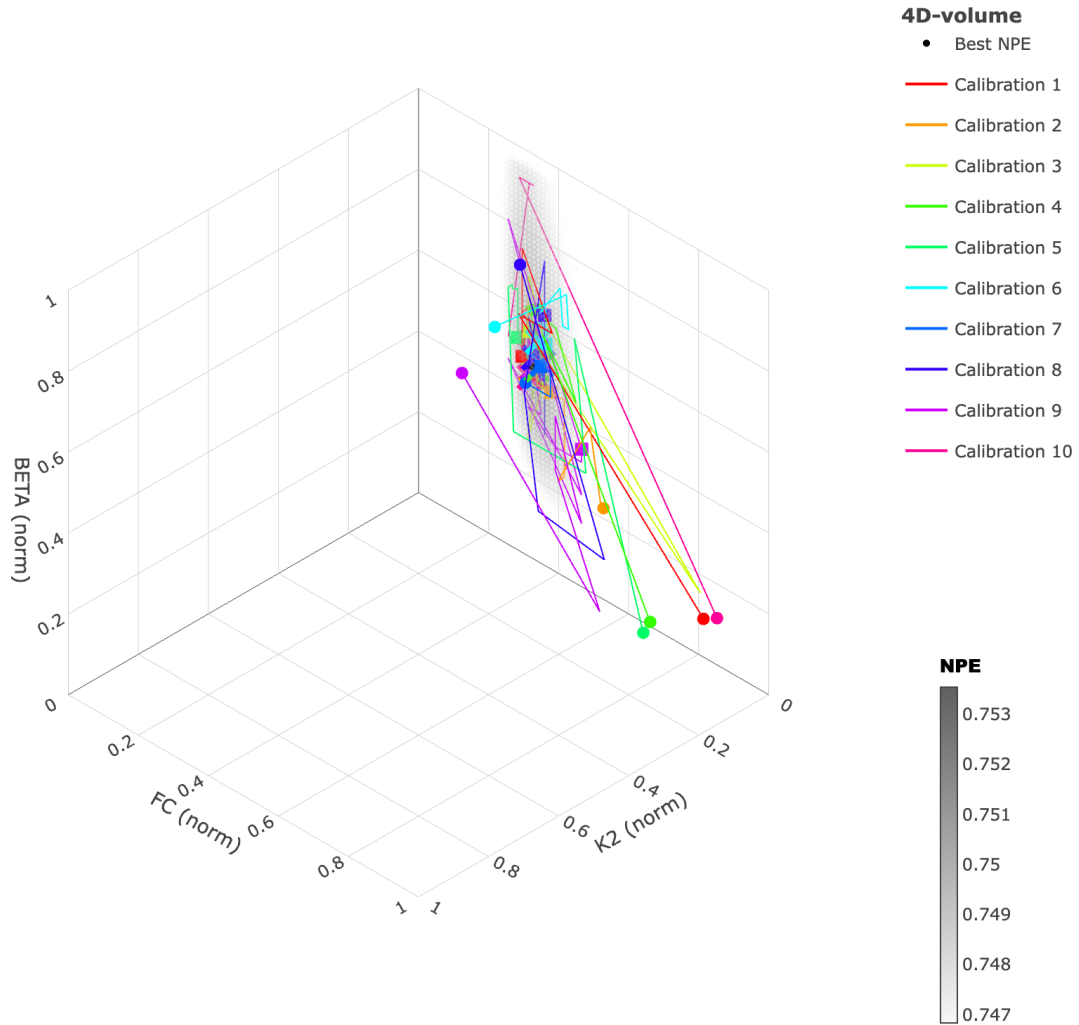
ES000356_4D_K: Persistence Diagram, top 5%



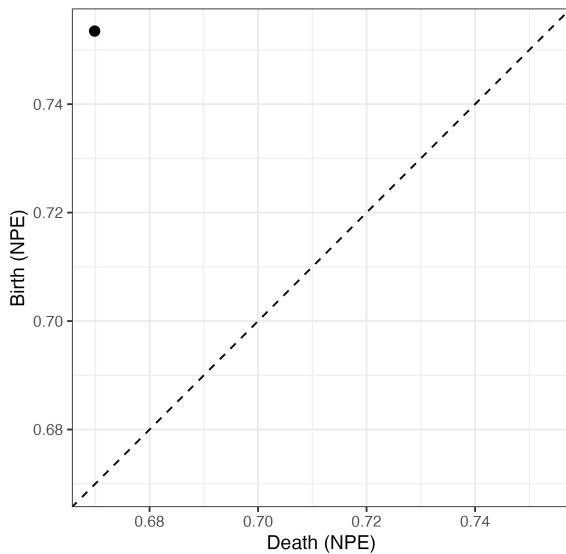
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.55071205	0.55080255	0.55080255	0.55102921	0.54744119
2	0.54889251	0.54951126	0.55102866	0.5510304	0.54744119
3	0.53493231	0.55061803	0.55109435	0.55110337	0.54744119
4	0.54952862	0.55046762	0.55067868	0.55109972	0.54744119
5	0.54927129	0.55077772	0.55106938	0.55107185	0.54744119
6	0.54618533	0.55095455	0.55103022	0.55108195	0.54744119
7	0.55065907	0.55083659	0.55083659	0.55096445	0.54744119
8	0.51454251	0.54571136	0.54581911	0.55102904	0.54744119
9	0.54095888	0.55024219	0.55024514	0.55024514	0.54744119
10	0.53907452	0.54495265	0.54961002	0.54972653	0.54744119

ES001323_4D_A, FC_K2_BETA_LP

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



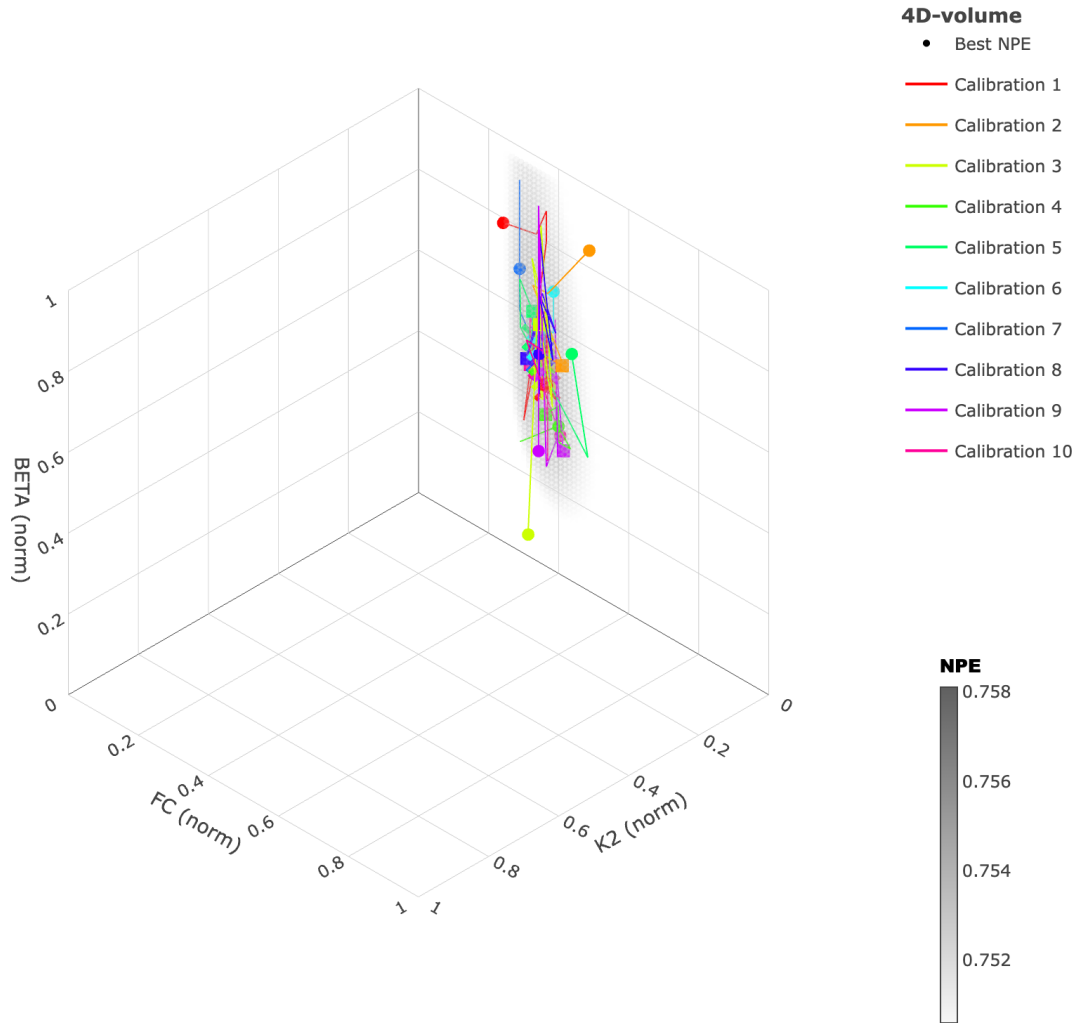
ES001323_4D_A: Persistence Diagram, top 5%



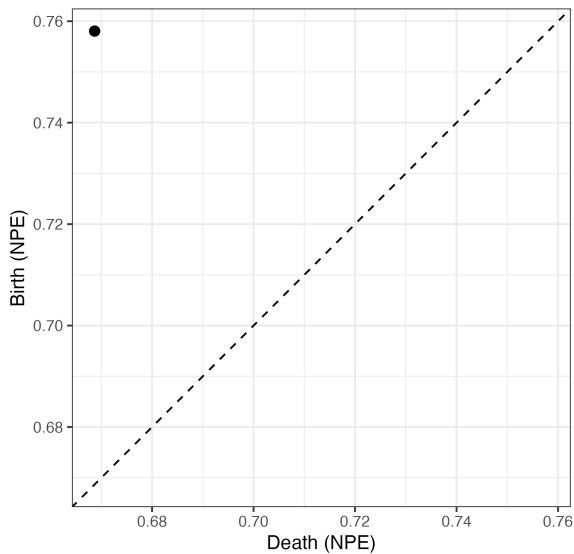
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.75156011	0.75218774	0.75347442	0.75362808	0.75353632
2	0.7515388	0.7534797	0.75365103	0.75366353	0.75353632
3	0.75330797	0.7535891	0.75366353	0.75366769	0.75353632
4	0.75234379	0.75357921	0.75359048	0.75359048	0.75353632
5	0.75135649	0.75344333	0.75366938	0.75367558	0.75353632
6	0.75235232	0.75285427	0.75294065	0.7532084	0.75353632
7	0.7483958	0.75233737	0.75289415	0.75323283	0.75353632
8	0.75199901	0.75273122	0.75318556	0.75358361	0.75353632
9	0.74746346	0.75350513	0.75361627	0.75365171	0.75353632
10	0.7523453	0.75342845	0.7535301	0.75360274	0.75353632

ES001323_4D_B, FC_K2_BETA_LP

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



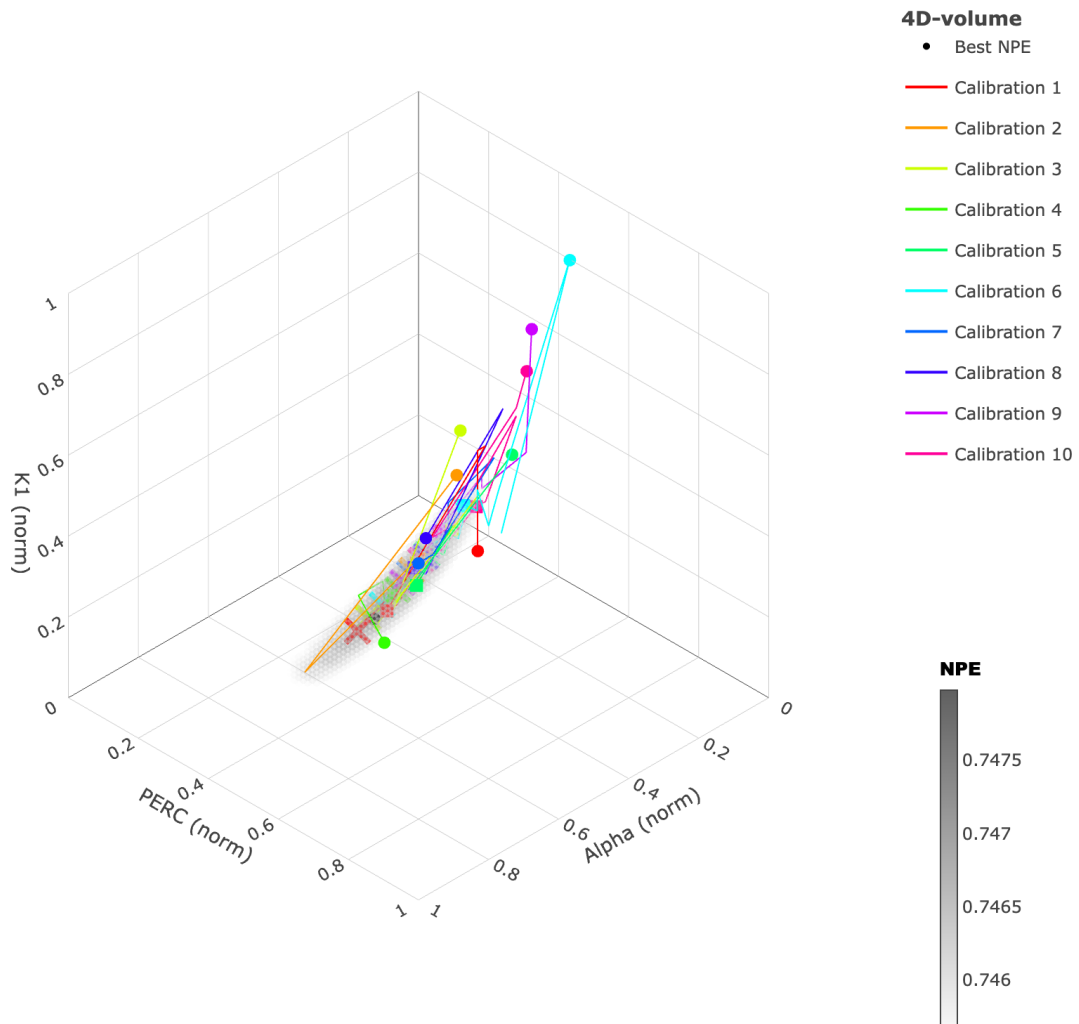
ES001323_4D_B: Persistence Diagram, top 5%



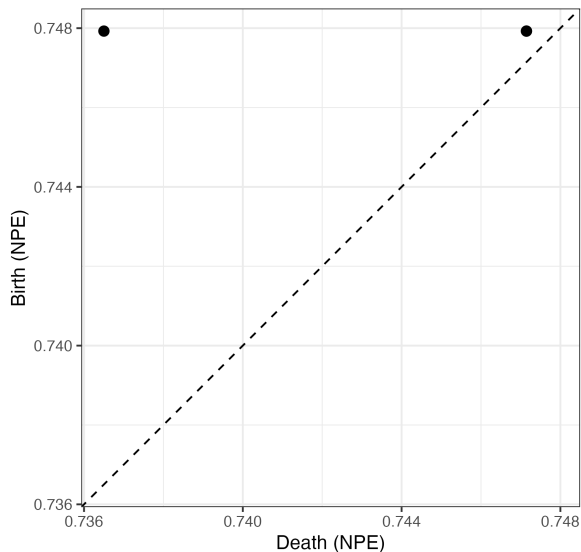
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.75689546	0.75774672	0.75778734	0.75792998	0.7581011
2	0.75396289	0.7558209	0.75685761	0.75808503	0.7581011
3	0.75134139	0.75745068	0.75795228	0.7580534	0.7581011
4	0.75730315	0.75788106	0.75788106	0.75794903	0.7581011
5	0.75701819	0.75732341	0.7578672	0.7579502	0.7581011
6	0.7578648	0.75795723	0.75801704	0.75807064	0.7581011
7	0.7579275	0.7579275	0.75807784	0.75810731	0.7581011
8	0.75489709	0.75703277	0.75736239	0.75804667	0.7581011
9	0.75566915	0.75743744	0.75778534	0.75782145	0.7581011
10	0.75735693	0.7574729	0.75799578	0.75810058	0.7581011

ES001323_4D_D, PERC_Alpha_K1_MAXBAS

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



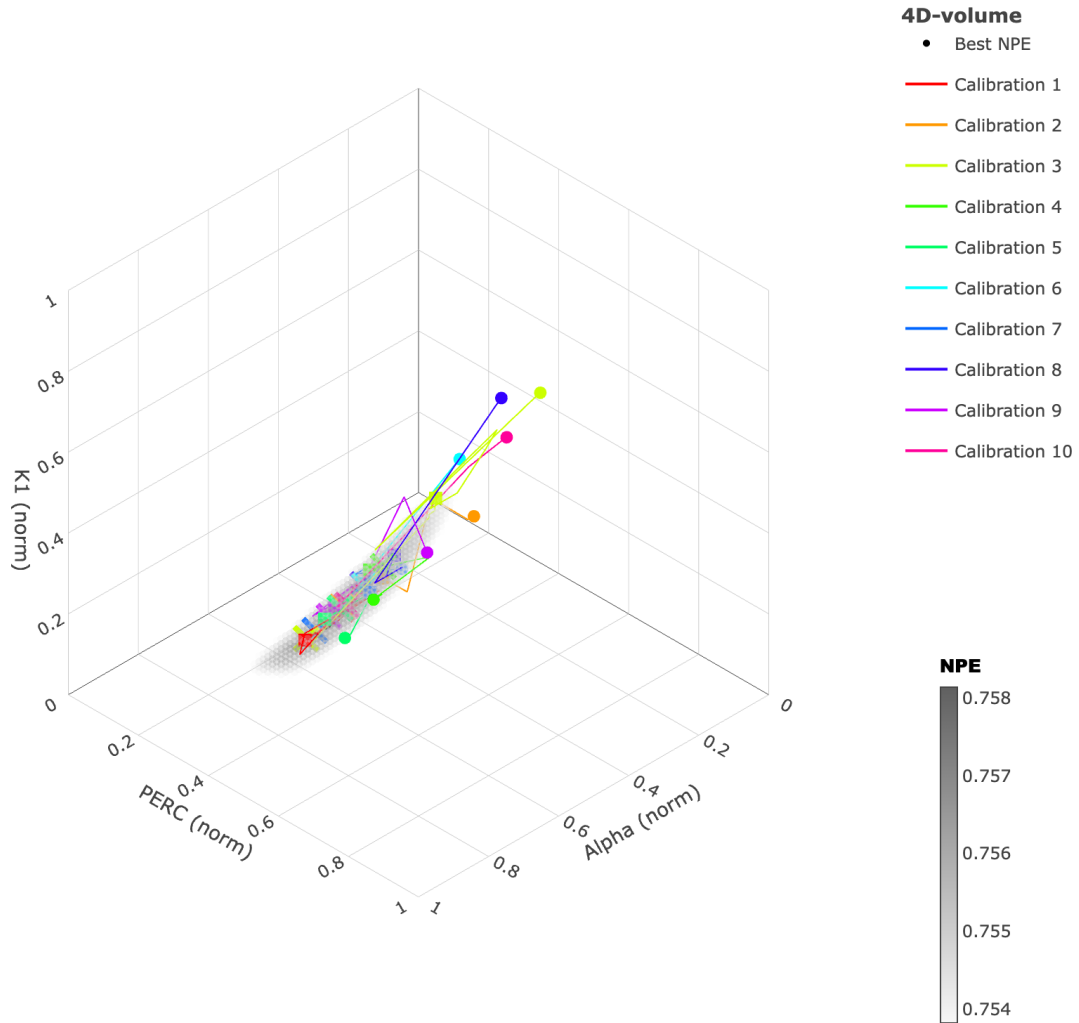
ES001323_4D_D: Persistence Diagram, top 5%



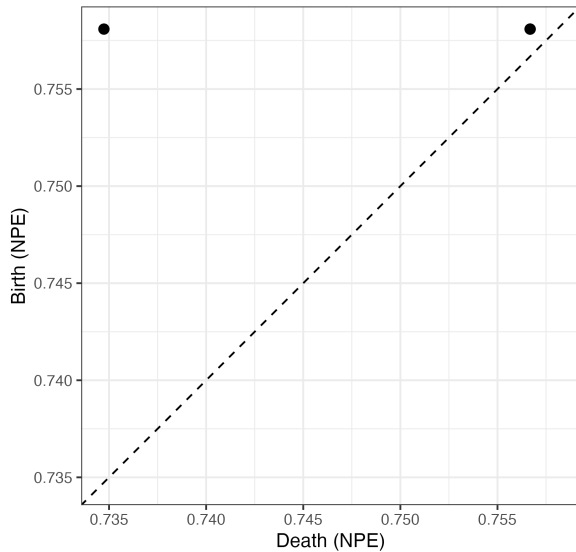
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.74700583	0.74715241	0.74762738	0.74790944	0.74797548
2	0.7473893	0.74790807	0.74792573	0.74793019	0.74797548
3	0.74683913	0.74763831	0.74784474	0.74801175	0.74797548
4	0.74737779	0.7479669	0.74797717	0.74799553	0.74797548
5	0.74573194	0.74636795	0.74740883	0.74760572	0.74797548
6	0.74586224	0.74736589	0.74775611	0.74793608	0.74797548
7	0.74690066	0.74756758	0.74790456	0.74792511	0.74797548
8	0.74652237	0.74745901	0.74758278	0.74765268	0.74797548
9	0.74681914	0.74791044	0.74791044	0.74796886	0.74797548
10	0.74604515	0.74747441	0.74760688	0.74773202	0.74797548

ES001323_4D_E, PERC_Alpha_K1_MAXBAS

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



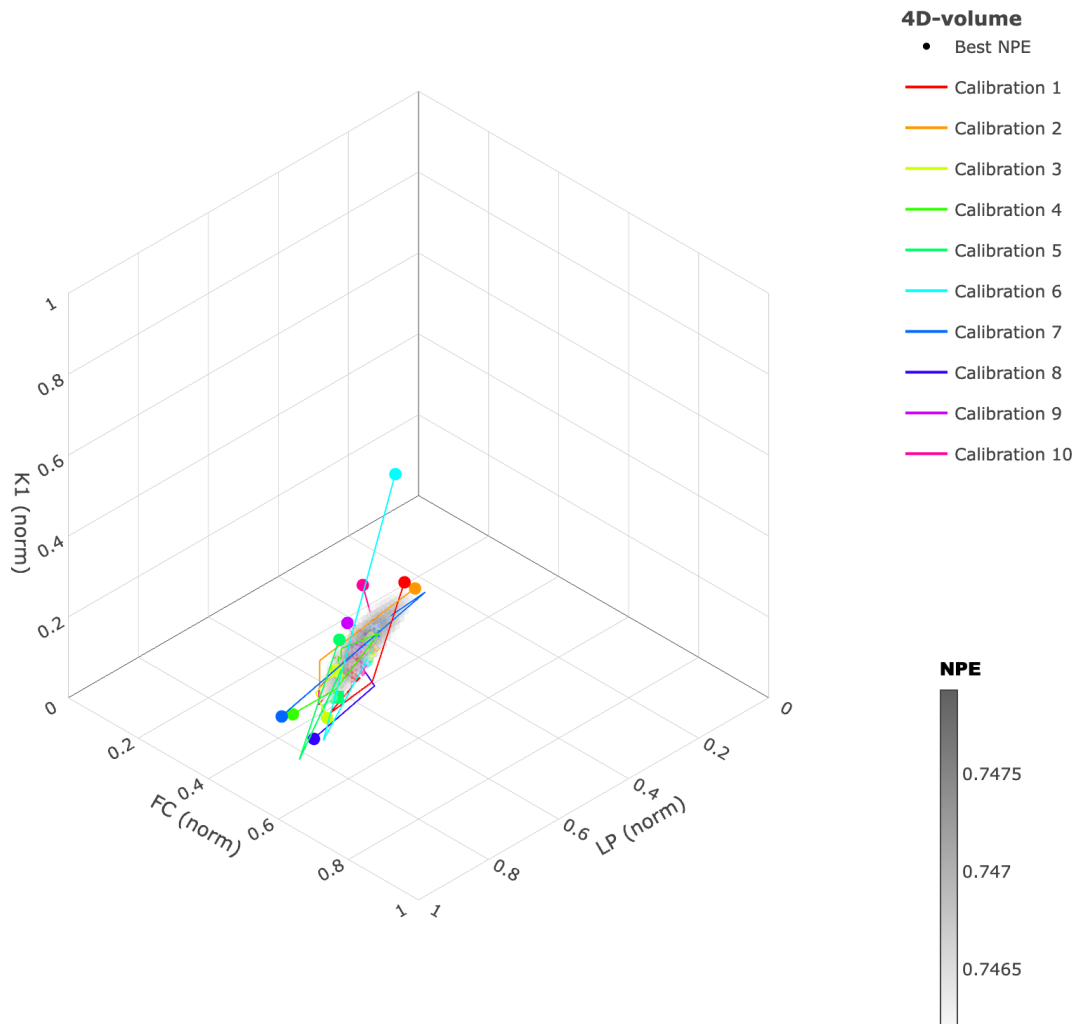
ES001323_4D_E: Persistence Diagram, top 5%



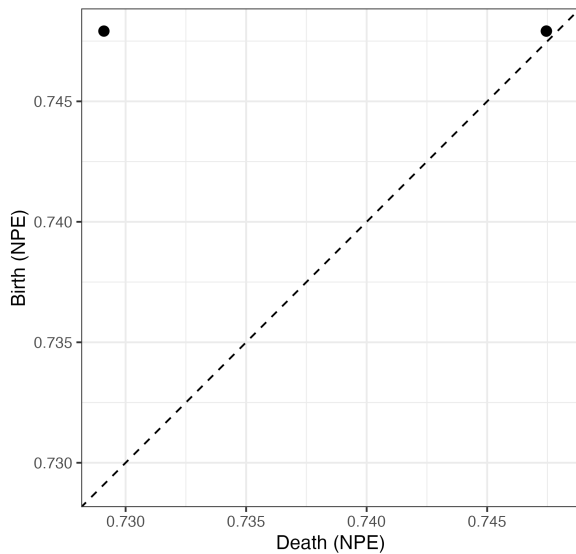
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.75620459	0.75814138	0.75814138	0.75814138	0.75813421
2	0.75524525	0.75811508	0.75812437	0.75814022	0.75813421
3	0.75412931	0.75513317	0.75714474	0.75811056	0.75813421
4	0.75668373	0.75715945	0.75717528	0.75721592	0.75813421
5	0.75691979	0.75810143	0.75811883	0.75812338	0.75813421
6	0.75765776	0.75780435	0.75780879	0.75788812	0.75813421
7	0.7568109	0.75765484	0.75789079	0.75812304	0.75813421
8	0.75680983	0.75758674	0.75775427	0.75778245	0.75813421
9	0.75697904	0.75776699	0.75810411	0.75815331	0.75813421
10	0.75779863	0.75803871	0.75808221	0.75808466	0.75813421

ES001323_4D_J, FC_LP_K1_SFCF

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



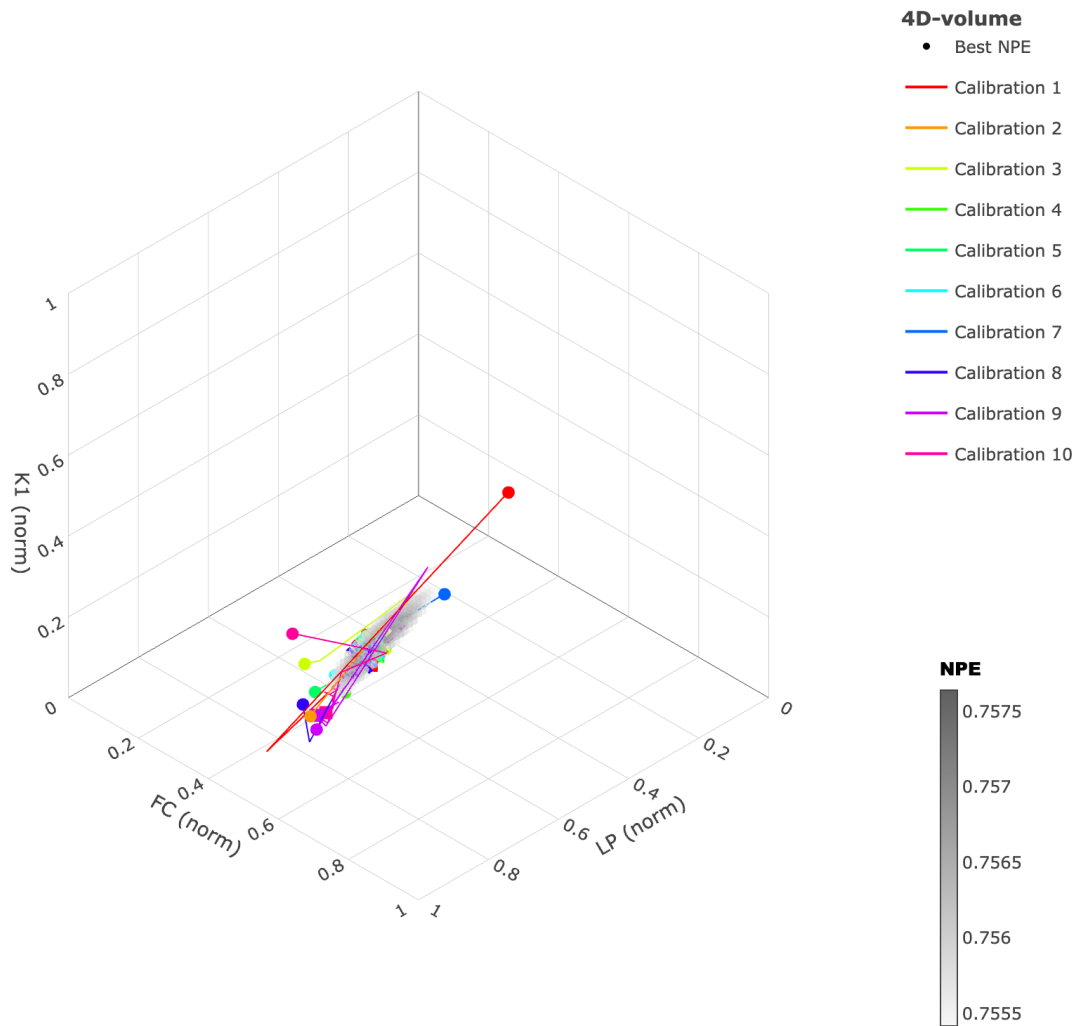
ES001323_4D_J: Persistence Diagram, top 5%



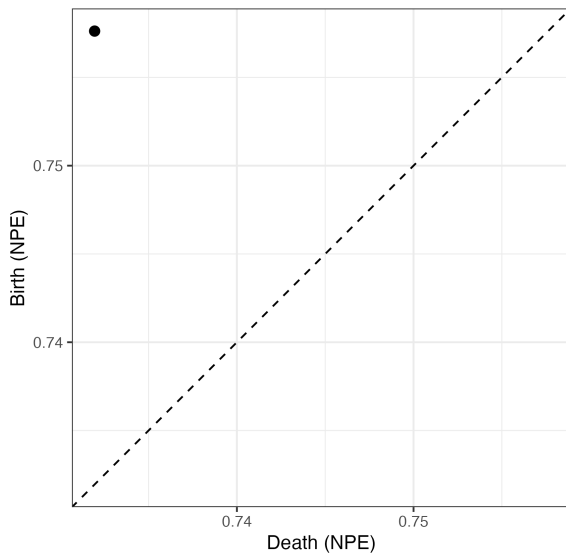
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.74747811	0.74771416	0.74773357	0.74773357	0.74792912
2	0.74776248	0.74791391	0.74792433	0.74795396	0.74792912
3	0.74631511	0.74752206	0.74787899	0.7479107	0.74792912
4	0.74714642	0.74788294	0.74788899	0.74789233	0.74792912
5	0.74635717	0.7473585	0.74777442	0.74788396	0.74792912
6	0.74785385	0.74788487	0.74788507	0.74788507	0.74792912
7	0.7475531	0.74791604	0.74798292	0.74798292	0.74792912
8	0.74790437	0.74795764	0.74799178	0.7480032	0.74792912
9	0.74754944	0.74783653	0.74784811	0.74785537	0.74792912
10	0.74722059	0.7476841	0.74770765	0.74781603	0.74792912

ES001323_4D_K, FC_LP_K1_SFCF

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



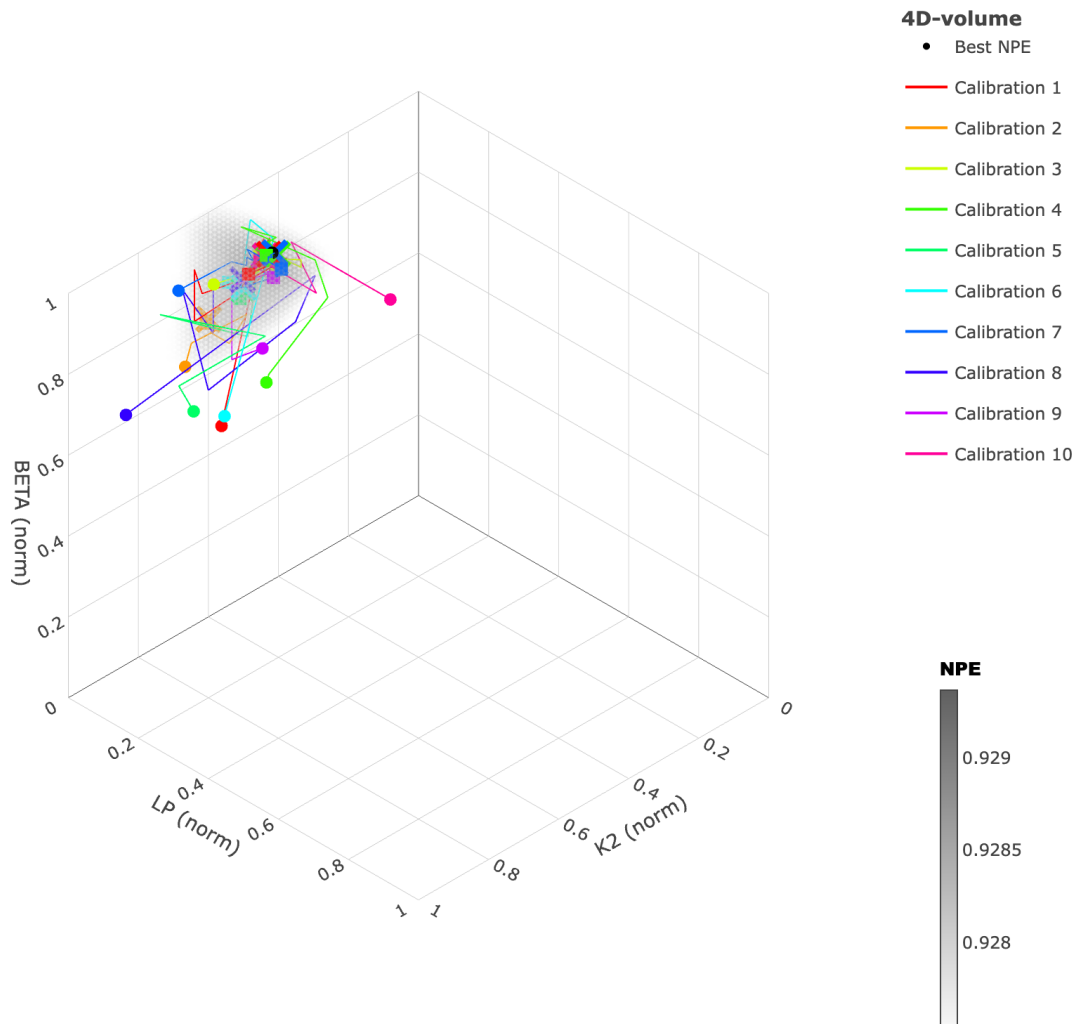
ES001323_4D_K: Persistence Diagram, top 5%



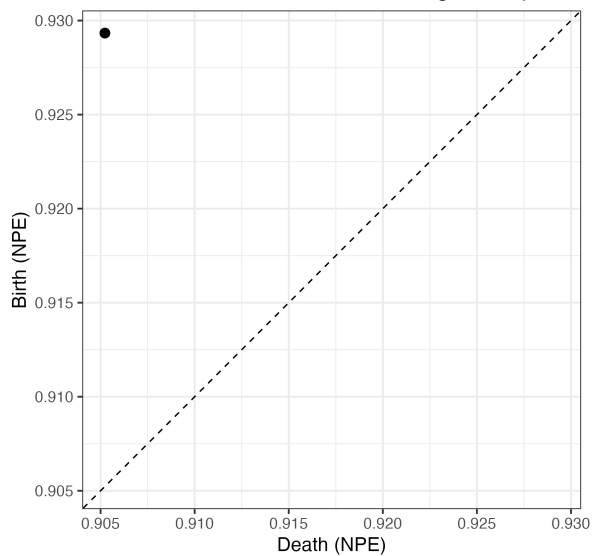
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.75618363	0.75754299	0.75760297	0.75760844	0.75763822
2	0.75759338	0.75762457	0.7576575	0.75766331	0.75763822
3	0.75727665	0.75750066	0.75763016	0.75763388	0.75763822
4	0.75598408	0.75760194	0.75760194	0.75764393	0.75763822
5	0.75751356	0.75760033	0.75760033	0.75764661	0.75763822
6	0.75718722	0.75764034	0.75764034	0.75764841	0.75763822
7	0.75693341	0.75758359	0.75758359	0.75759758	0.75763822
8	0.75709778	0.75731038	0.75741177	0.75746633	0.75763822
9	0.75390363	0.75738459	0.75757617	0.75763808	0.75763822
10	0.75441807	0.75579825	0.75761443	0.75767286	0.75763822

FR000672_4D_A, LP_K2_BETA_FC

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



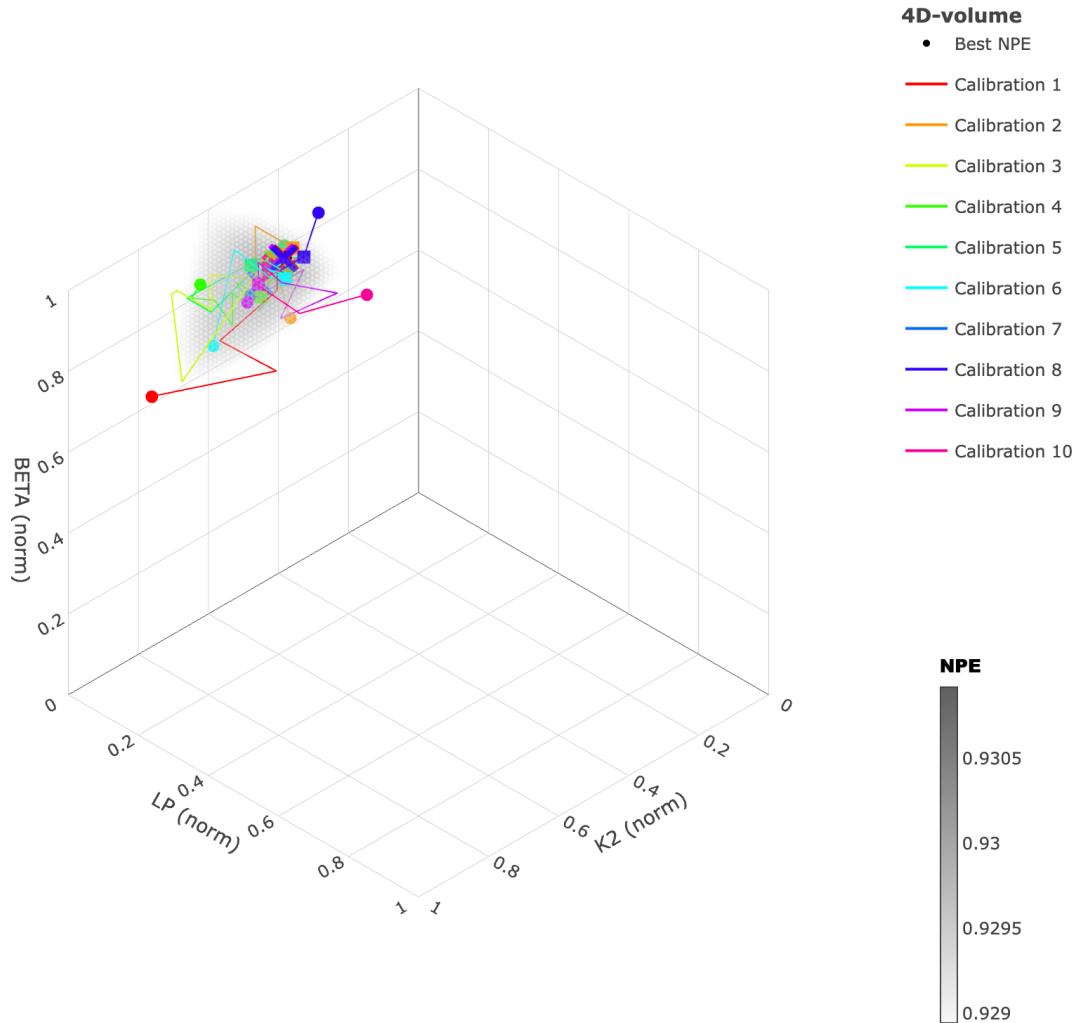
FR000672_4D_A: Persistence Diagram, top 5%



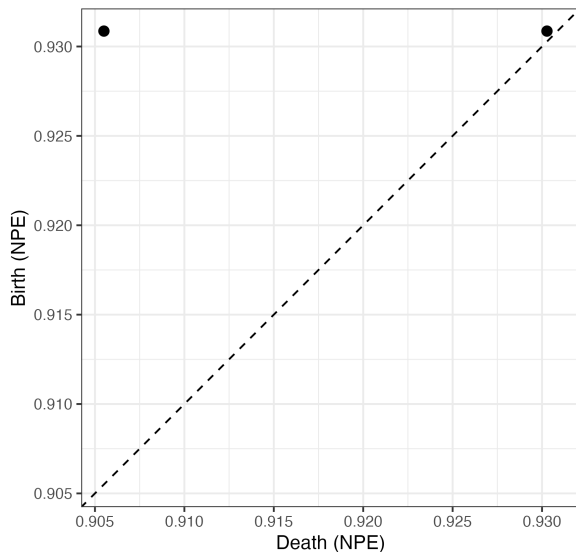
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.92884632	0.92934274	0.92935754	0.92936057	0.92936303
2	0.92879165	0.9288163	0.92882823	0.92882914	0.92936303
3	0.92926338	0.92933237	0.92933259	0.92933392	0.92936303
4	0.92932759	0.92932759	0.92936808	0.92937308	0.92936303
5	0.92901265	0.92909064	0.92911988	0.92912403	0.92936303
6	0.92901697	0.92911422	0.92913443	0.92914391	0.92936303
7	0.92908864	0.92928275	0.92937065	0.92937319	0.92936303
8	0.92886927	0.92906947	0.9290878	0.92914162	0.92936303
9	0.92913668	0.92929825	0.92930959	0.92932194	0.92936303
10	0.92930143	0.92932478	0.92933459	0.92933661	0.92936303

FR000672_4D_B, LP_K2_BETA_FC

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



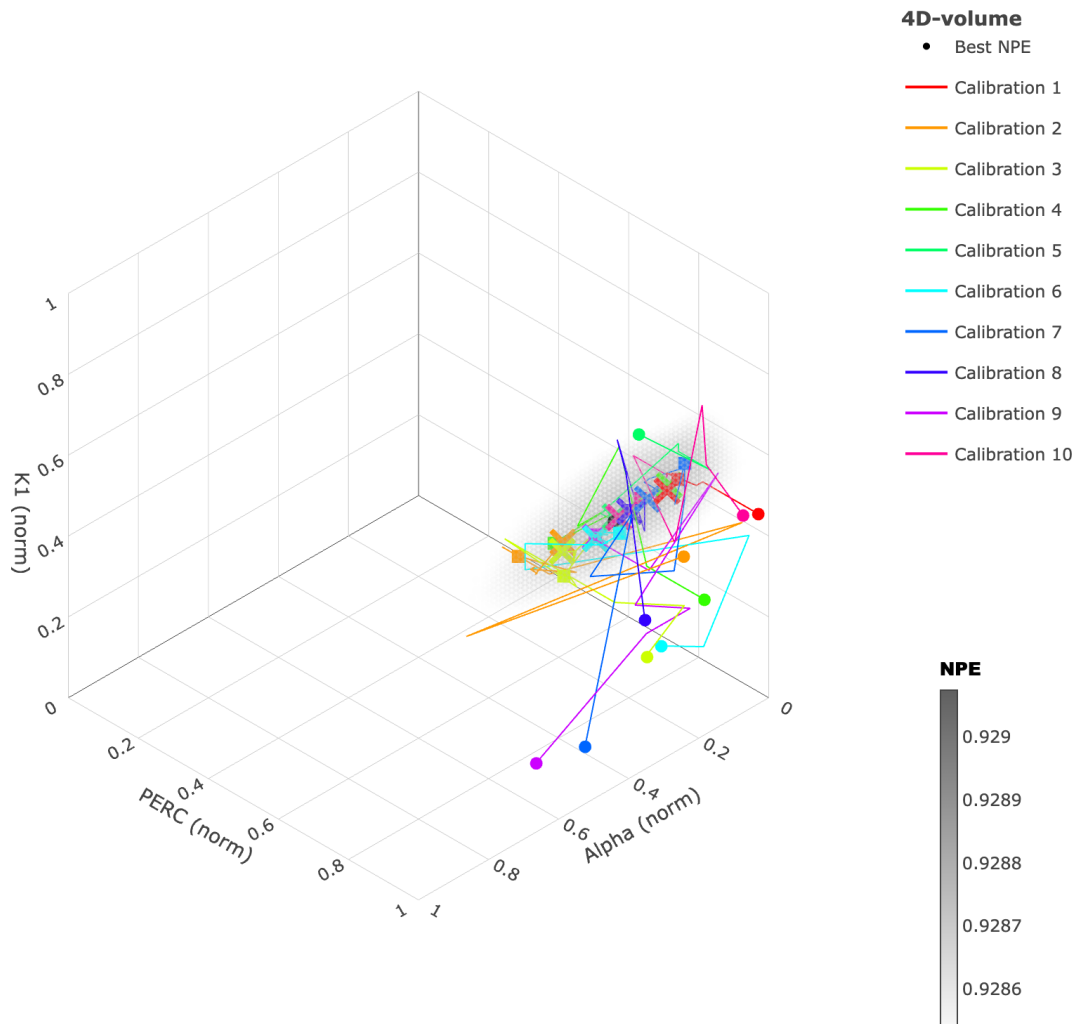
FR000672_4D_B: Persistence Diagram, top 5%



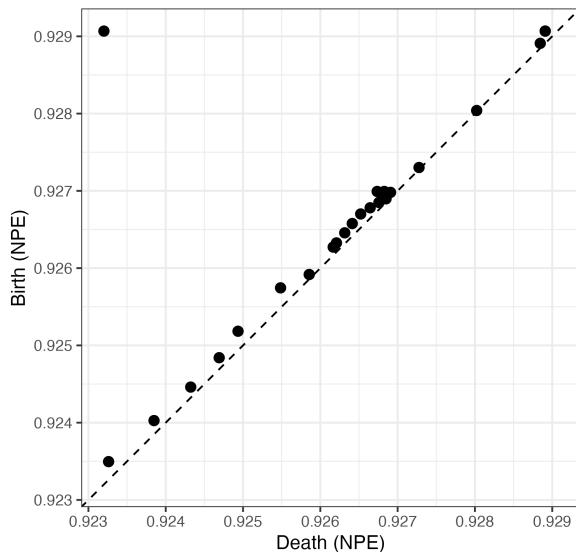
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.93084754	0.9308976	0.93090579	0.93092131	0.93091636
2	0.93022783	0.93085488	0.93088792	0.93089981	0.93091636
3	0.93073341	0.93074902	0.93077967	0.93083285	0.93091636
4	0.93064776	0.93069313	0.93073998	0.93086037	0.93091636
5	0.93052407	0.93088454	0.93088784	0.93090138	0.93091636
6	0.93040877	0.9306659	0.93090263	0.93090737	0.93091636
7	0.93068061	0.93075027	0.93076294	0.93076463	0.93091636
8	0.93045721	0.93085128	0.93087661	0.93092552	0.93091636
9	0.9304753	0.9308854	0.9308854	0.93091126	0.93091636
10	0.93077969	0.93086781	0.93086781	0.93086952	0.93091636

FR000672_4D_D, PERC_Alpha_K1_MAXBAS

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



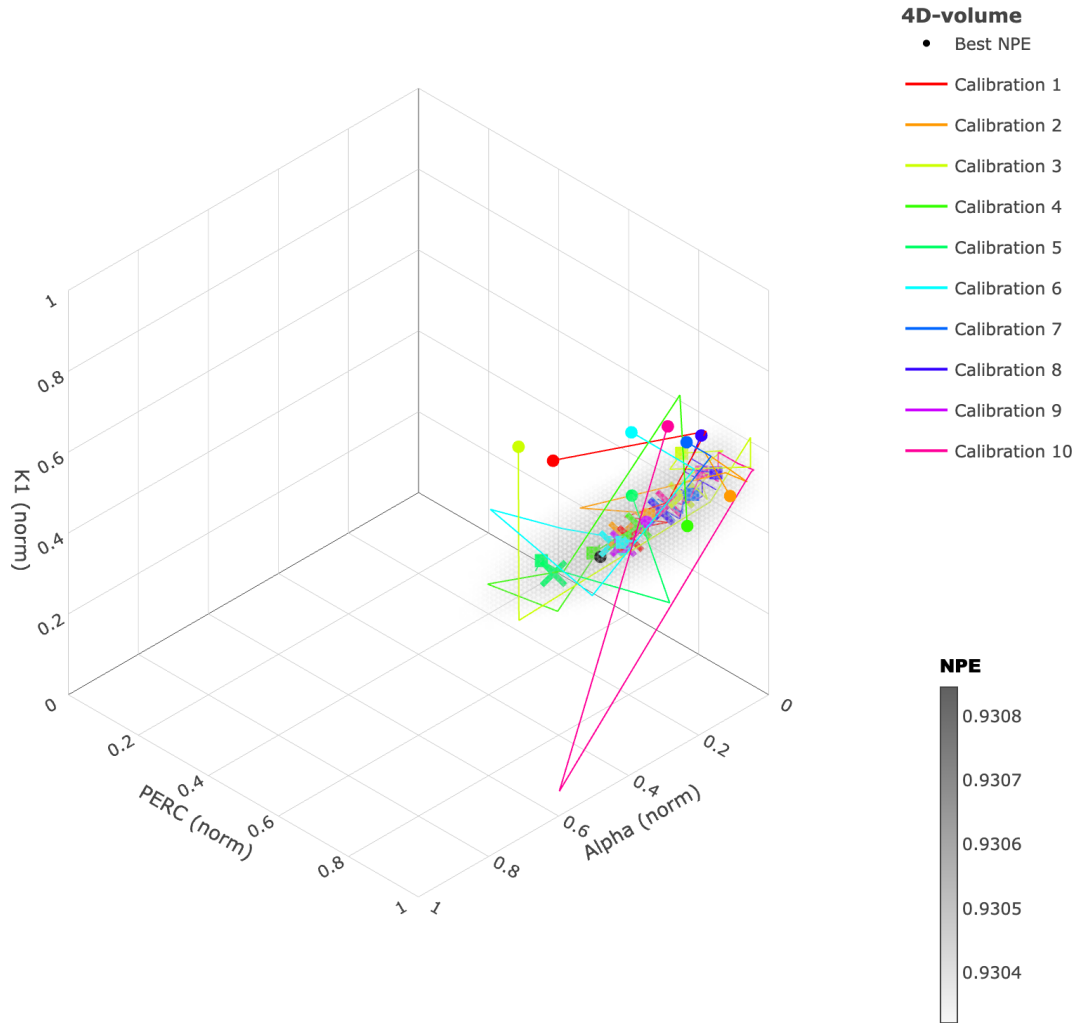
FR000672_4D_D: Persistence Diagram, top 5%



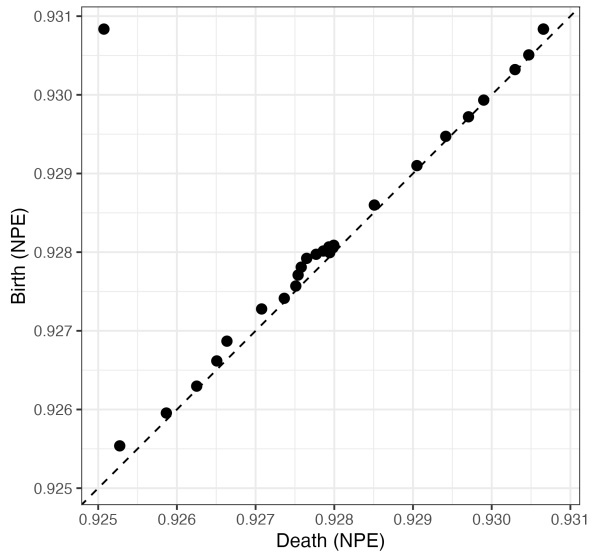
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.92897058	0.92897831	0.92899938	0.92900263	0.92907325
2	0.9287436	0.92894589	0.92896222	0.92903648	0.92907325
3	0.92890913	0.92903872	0.92904219	0.9290527	0.92907325
4	0.92895742	0.92895742	0.92899051	0.92900371	0.92907325
5	0.92899777	0.92907128	0.92907581	0.92908094	0.92907325
6	0.92892759	0.92906608	0.92907602	0.92907903	0.92907325
7	0.92889604	0.9289705	0.92901405	0.929039	0.92907325
8	0.92903841	0.92906897	0.9290705	0.9290705	0.92907325
9	0.92898158	0.92907244	0.92907584	0.92907985	0.92907325
10	0.92902599	0.92902858	0.92904308	0.92907065	0.92907325

FR000672_4D_E, PERC_Alpha_K1_MAXBAS

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



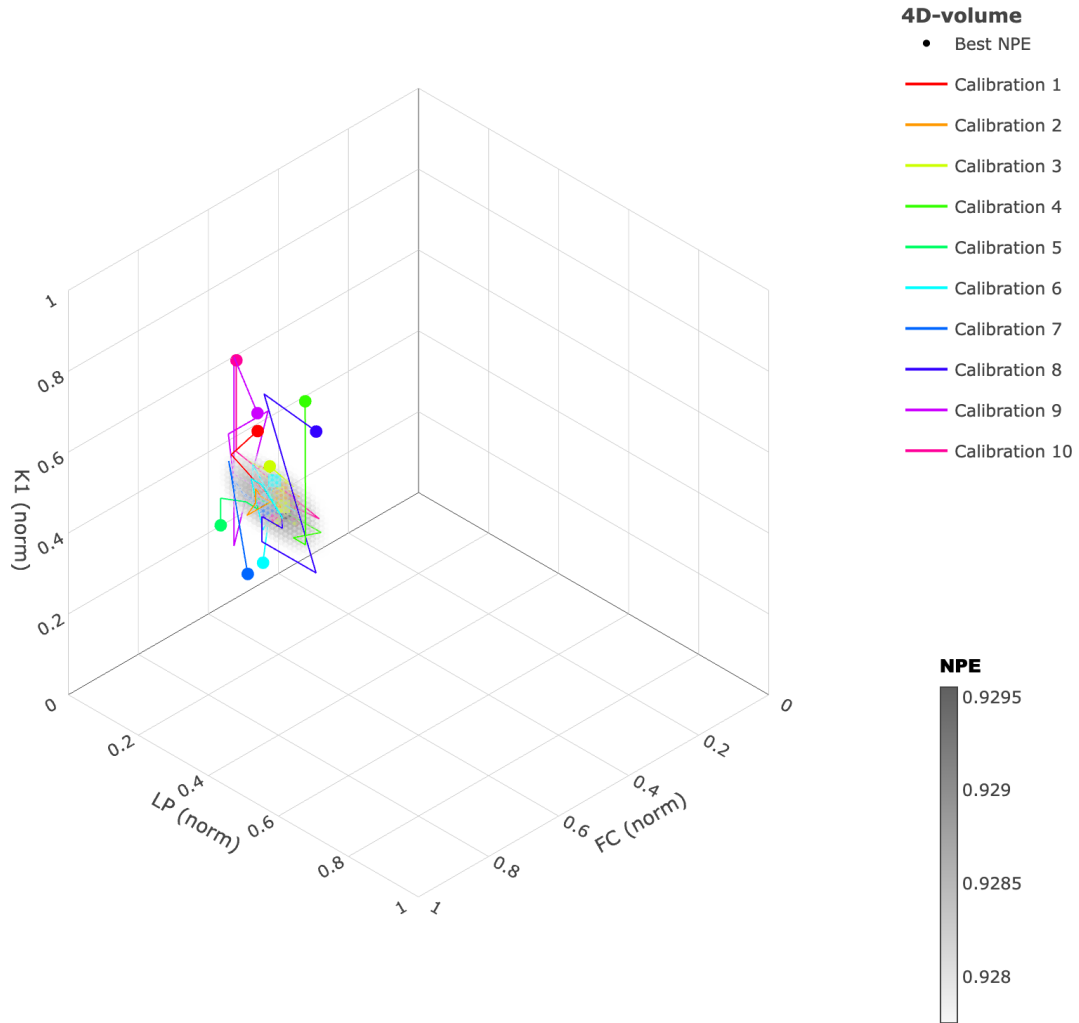
FR000672_4D_E: Persistence Diagram, top 5%



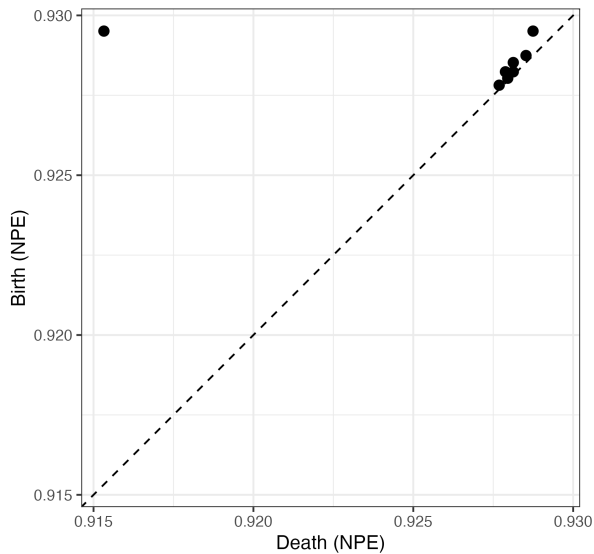
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.93078208	0.93080815	0.93082979	0.93083544	0.93084461
2	0.93070015	0.93081287	0.93082047	0.93083317	0.93084461
3	0.93044006	0.93070205	0.93070205	0.93072709	0.93084461
4	0.93069427	0.93079666	0.93080831	0.93080959	0.93084461
5	0.93071459	0.93079085	0.93079762	0.9307985	0.93084461
6	0.93064249	0.93082272	0.93083636	0.93084639	0.93084461
7	0.93068486	0.93076064	0.93077009	0.93077361	0.93084461
8	0.93059176	0.93066736	0.93075108	0.93077259	0.93084461
9	0.93082393	0.93082513	0.93083905	0.93083922	0.93084461
10	0.93061601	0.93072084	0.93073082	0.93075958	0.93084461

FR000672_4D_J, LP_FC_K1_TT

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



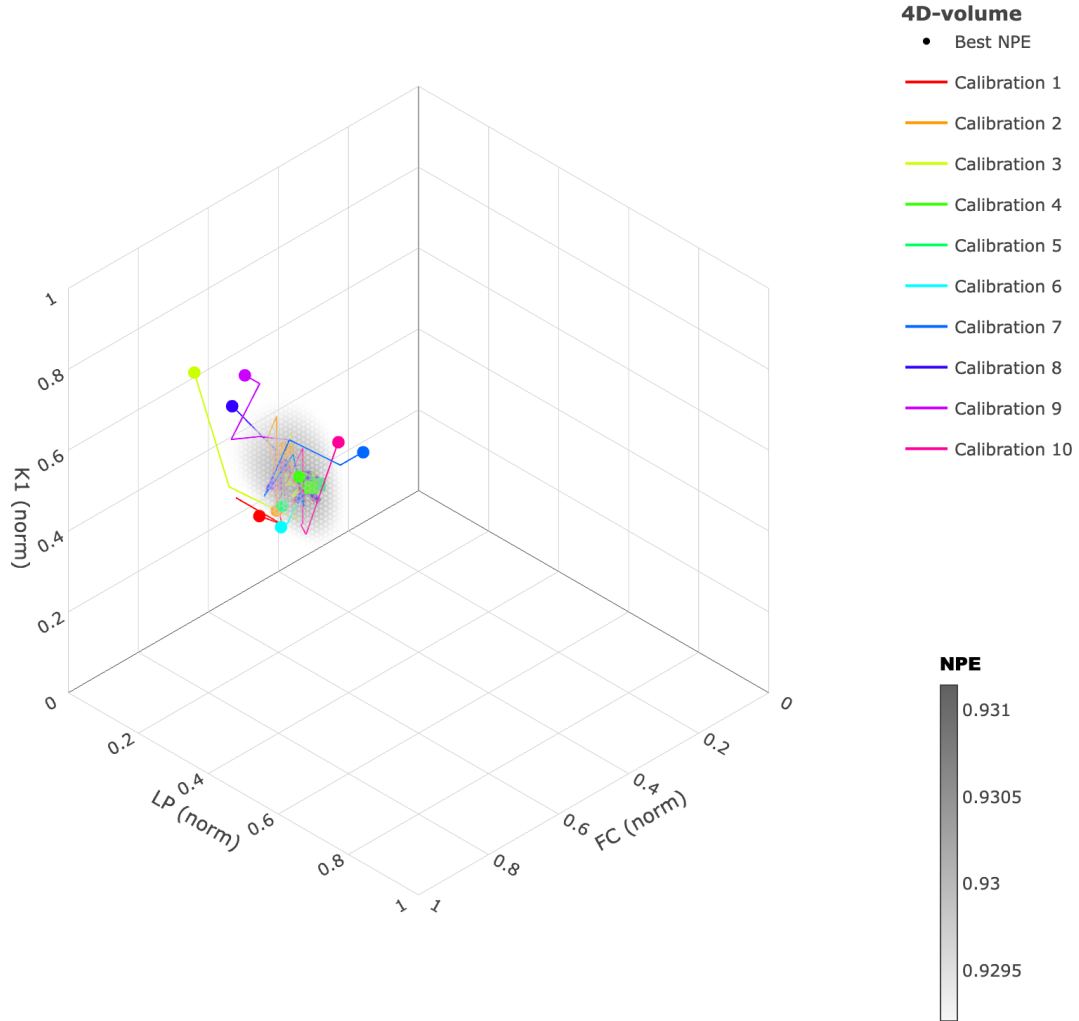
FR000672_4D_J: Persistence Diagram, top 5%



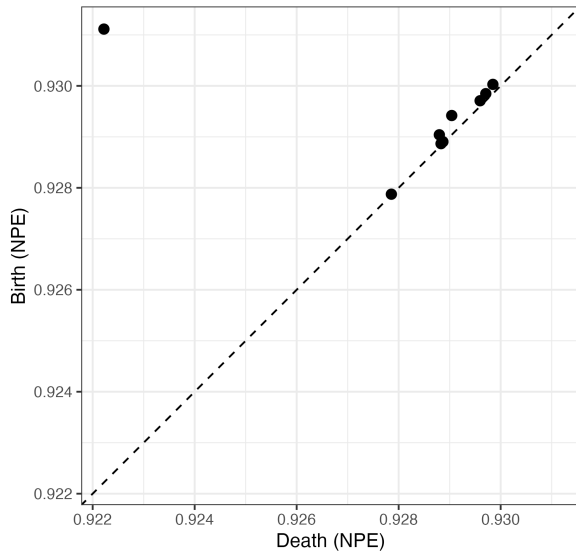
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.92883641	0.92952422	0.92954297	0.92955328	0.92955186
2	0.92910604	0.92951444	0.92956476	0.92956476	0.92955186
3	0.92885155	0.92932158	0.92949059	0.92957215	0.92955186
4	0.92936763	0.92950316	0.92952025	0.92952822	0.92955186
5	0.92925566	0.92942953	0.92947606	0.92952236	0.92955186
6	0.92865117	0.929495	0.92952596	0.92956591	0.92955186
7	0.92860387	0.92937964	0.92952215	0.92952304	0.92955186
8	0.92946391	0.92950568	0.92950973	0.92952144	0.92955186
9	0.92929725	0.92951393	0.92951393	0.9295331	0.92955186
10	0.92951047	0.92956521	0.92956882	0.92956882	0.92955186

FR000672_4D_K, LP_FC_K1_TT

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



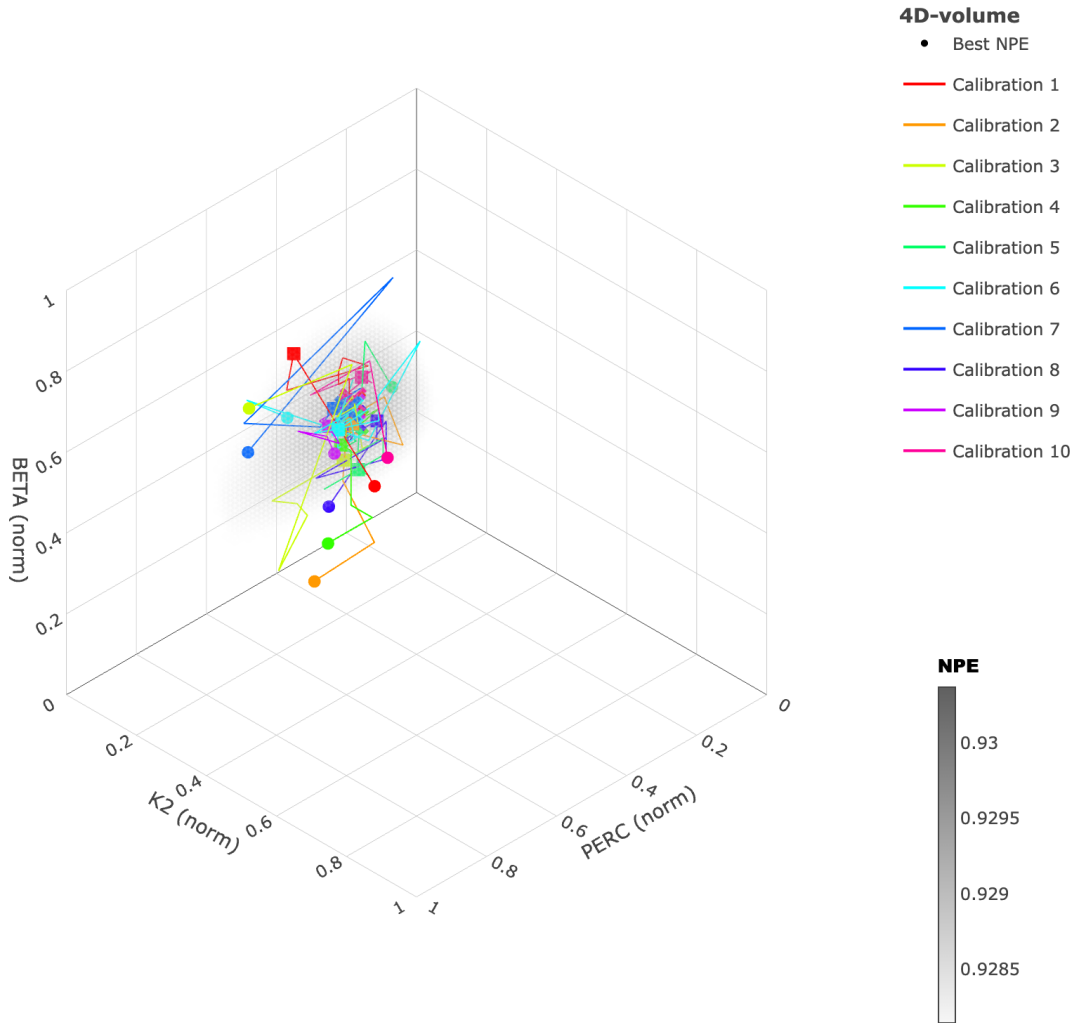
FR000672_4D_K: Persistence Diagram, top 5%



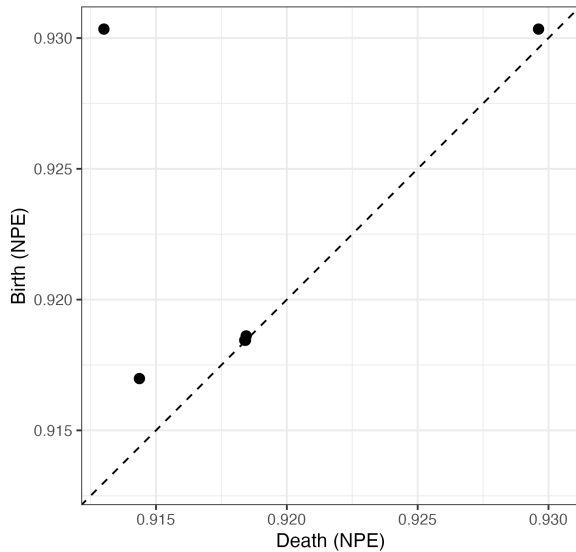
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.93058725	0.93113096	0.93114067	0.93115974	0.93114266
2	0.93044491	0.93114211	0.93114985	0.9311533	0.93114266
3	0.93075799	0.931006	0.93115207	0.93116024	0.93114266
4	0.93075964	0.93105899	0.93114538	0.93115729	0.93114266
5	0.93100023	0.93114433	0.93116217	0.93117044	0.93114266
6	0.93062602	0.93114466	0.93116382	0.93116615	0.93114266
7	0.93069512	0.93106122	0.93110891	0.93116223	0.93114266
8	0.93066718	0.93100668	0.93114577	0.93115579	0.93114266
9	0.93060702	0.93110979	0.93112221	0.93116988	0.93114266
10	0.93044329	0.93113817	0.93115826	0.93115826	0.93114266

FR000730_4D_A, K2_PERC_BETA_LP

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



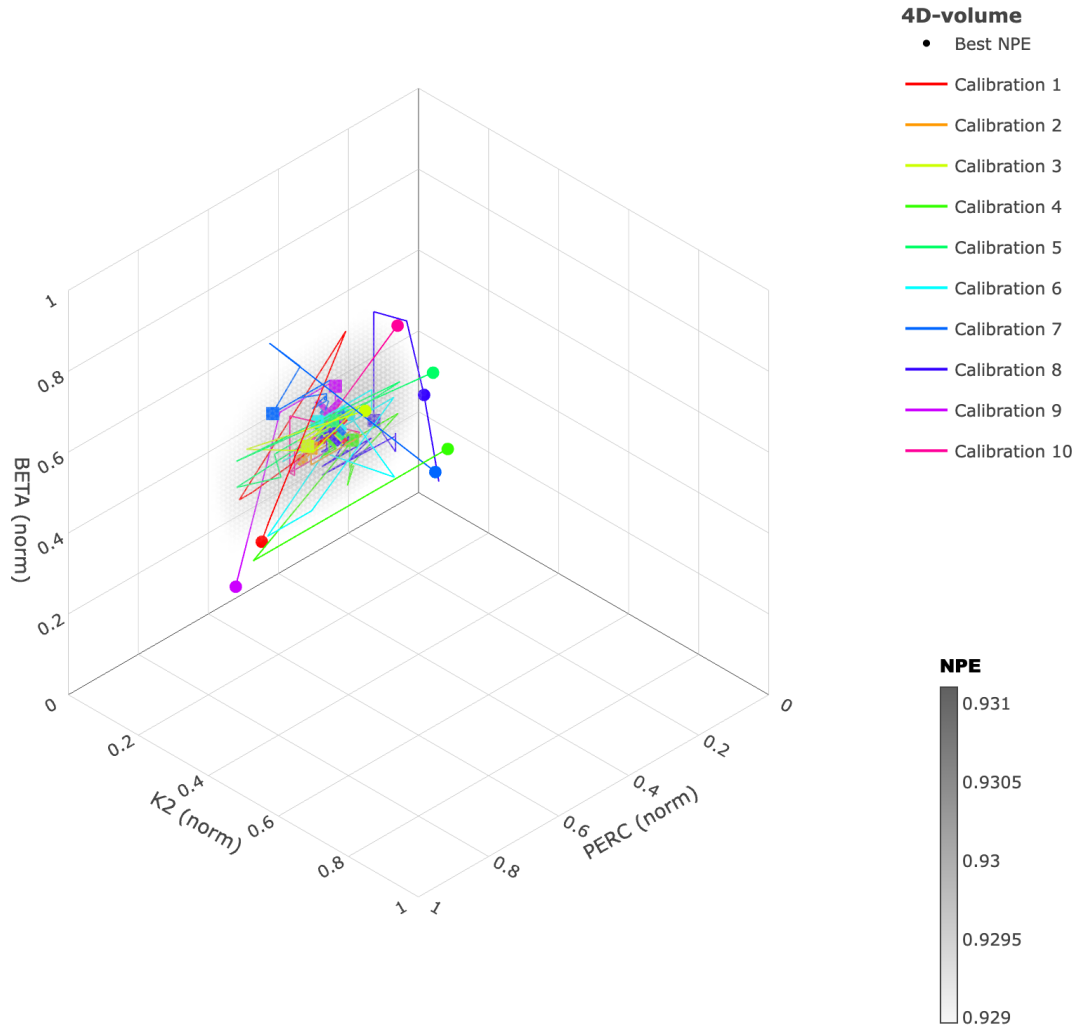
FR000730_4D_A: Persistence Diagram, top 5%



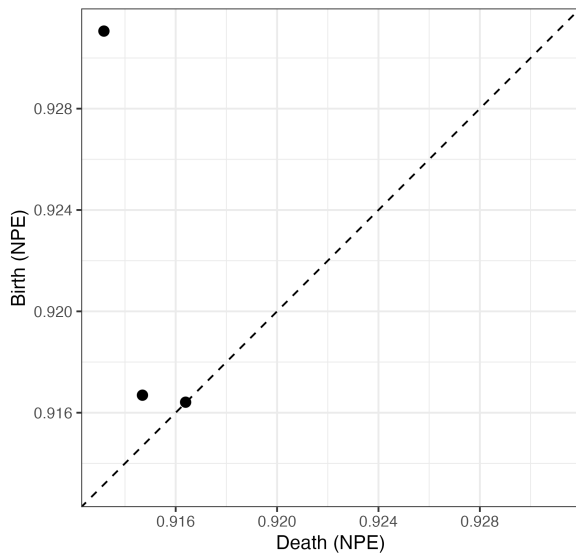
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.92754186	0.92995639	0.93032907	0.93035054	0.93036769
2	0.93029396	0.93034219	0.93034905	0.93037127	0.93036769
3	0.92936022	0.92981464	0.93035523	0.93037819	0.93036769
4	0.92995181	0.9300787	0.93033224	0.9303501	0.93036769
5	0.92866844	0.92979	0.93011915	0.93033146	0.93036769
6	0.9298131	0.93028677	0.93035206	0.93037887	0.93036769
7	0.93009923	0.93020791	0.93035586	0.93038316	0.93036769
8	0.92994081	0.93013369	0.93028536	0.93036945	0.93036769
9	0.93011479	0.93036634	0.93038507	0.93038607	0.93036769
10	0.93003594	0.93027315	0.93027436	0.93034701	0.93036769

FR000730_4D_B, K2_PERC_BETA_LP

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



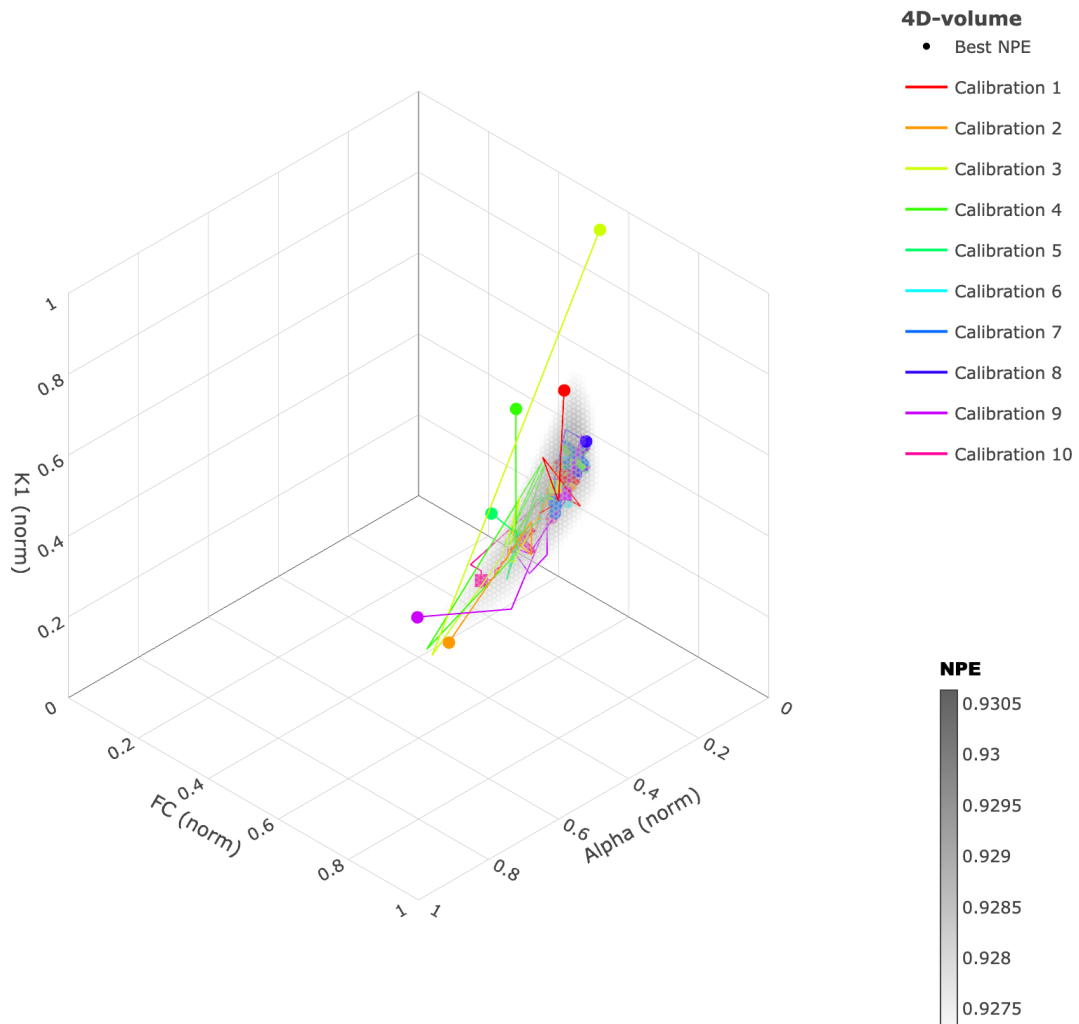
FR000730_4D_B: Persistence Diagram, top 5%



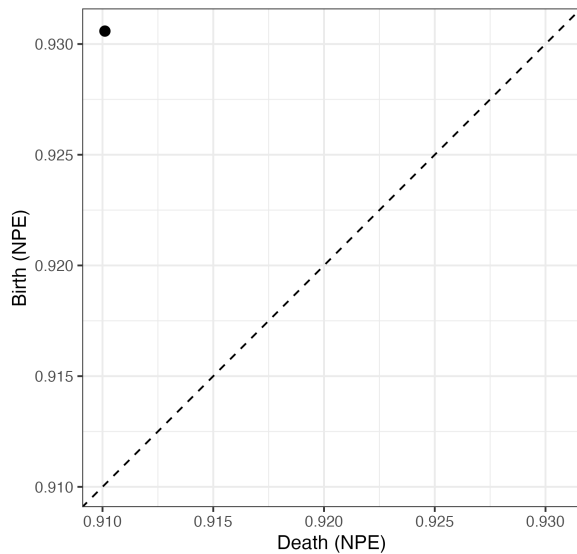
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.93100247	0.93109959	0.93109959	0.93109959	0.93110223
2	0.93100927	0.93109648	0.93110328	0.93110328	0.93110223
3	0.93081476	0.93107891	0.9311051	0.9311051	0.93110223
4	0.93084593	0.93089552	0.93091155	0.93109597	0.93110223
5	0.93052351	0.93100555	0.93107769	0.93110627	0.93110223
6	0.93090316	0.93096549	0.93099286	0.93105511	0.93110223
7	0.92988817	0.93069437	0.93097007	0.93108418	0.93110223
8	0.92888038	0.93068182	0.93090129	0.93109008	0.93110223
9	0.93061196	0.93093504	0.93096697	0.93100292	0.93110223
10	0.9308554	0.9310326	0.93108027	0.93110756	0.93110223

FR000730_4D_D, FC_Alpha_K1_MAXBAS

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



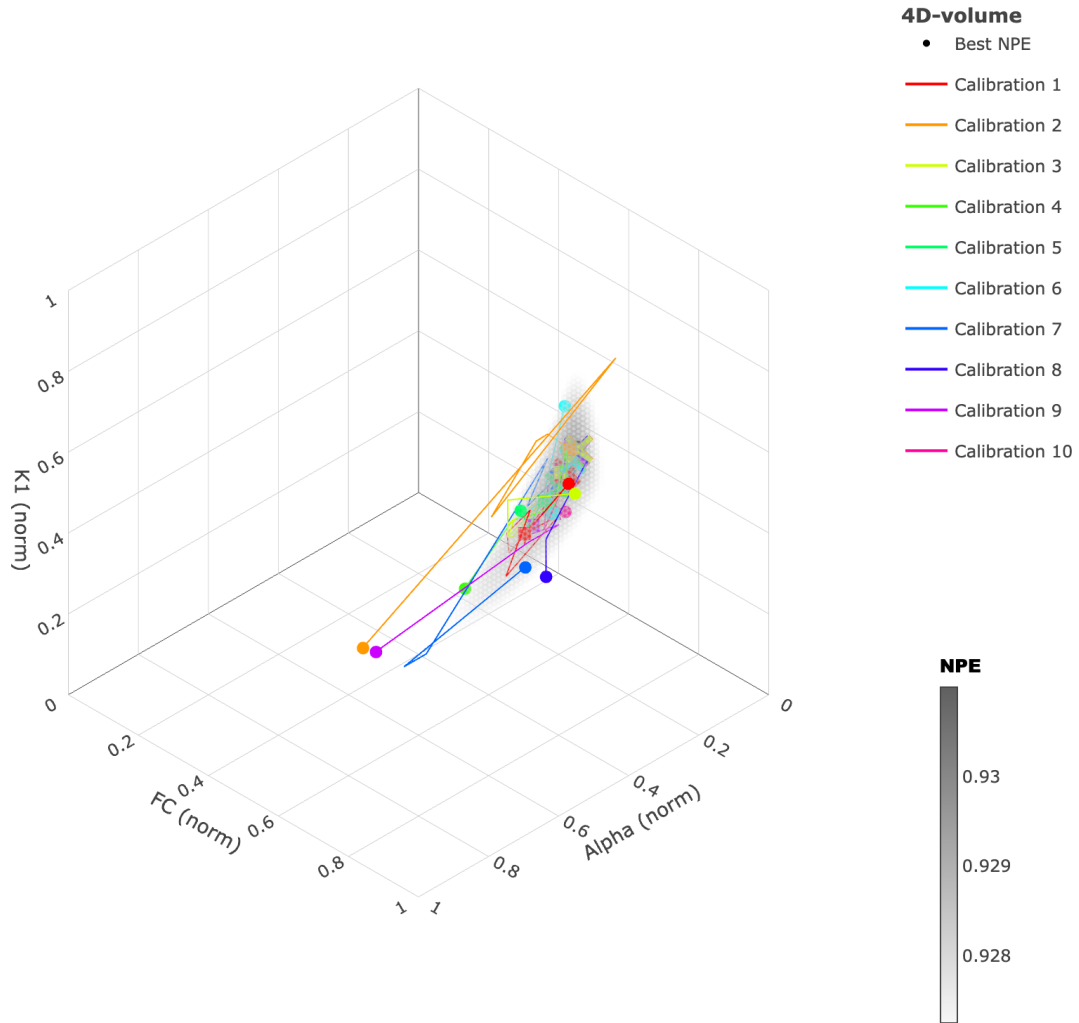
FR000730_4D_D: Persistence Diagram, top 5%



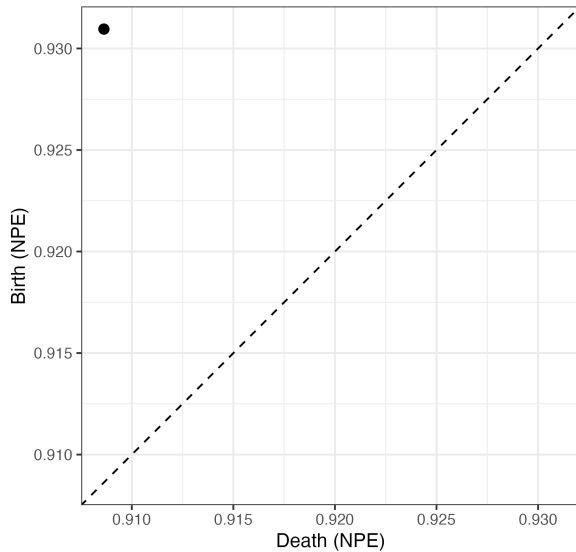
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.93047733	0.93056657	0.93058193	0.93058372	0.93063106
2	0.93041152	0.93055337	0.93056498	0.93056761	0.93063106
3	0.93032768	0.93055469	0.93057335	0.93061798	0.93063106
4	0.92977369	0.93035306	0.93048005	0.93060135	0.93063106
5	0.93034679	0.93054385	0.93061912	0.9306196	0.93063106
6	0.93035304	0.93059975	0.93060617	0.93062361	0.93063106
7	0.93026151	0.9305333	0.93056425	0.93061151	0.93063106
8	0.93032863	0.93056731	0.93059808	0.93061681	0.93063106
9	0.93025946	0.93046661	0.93058765	0.93062324	0.93063106
10	0.92914952	0.92932919	0.92950761	0.92993384	0.93063106

FR000730_4D_E, FC_Alpha_K1_MAXBAS

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



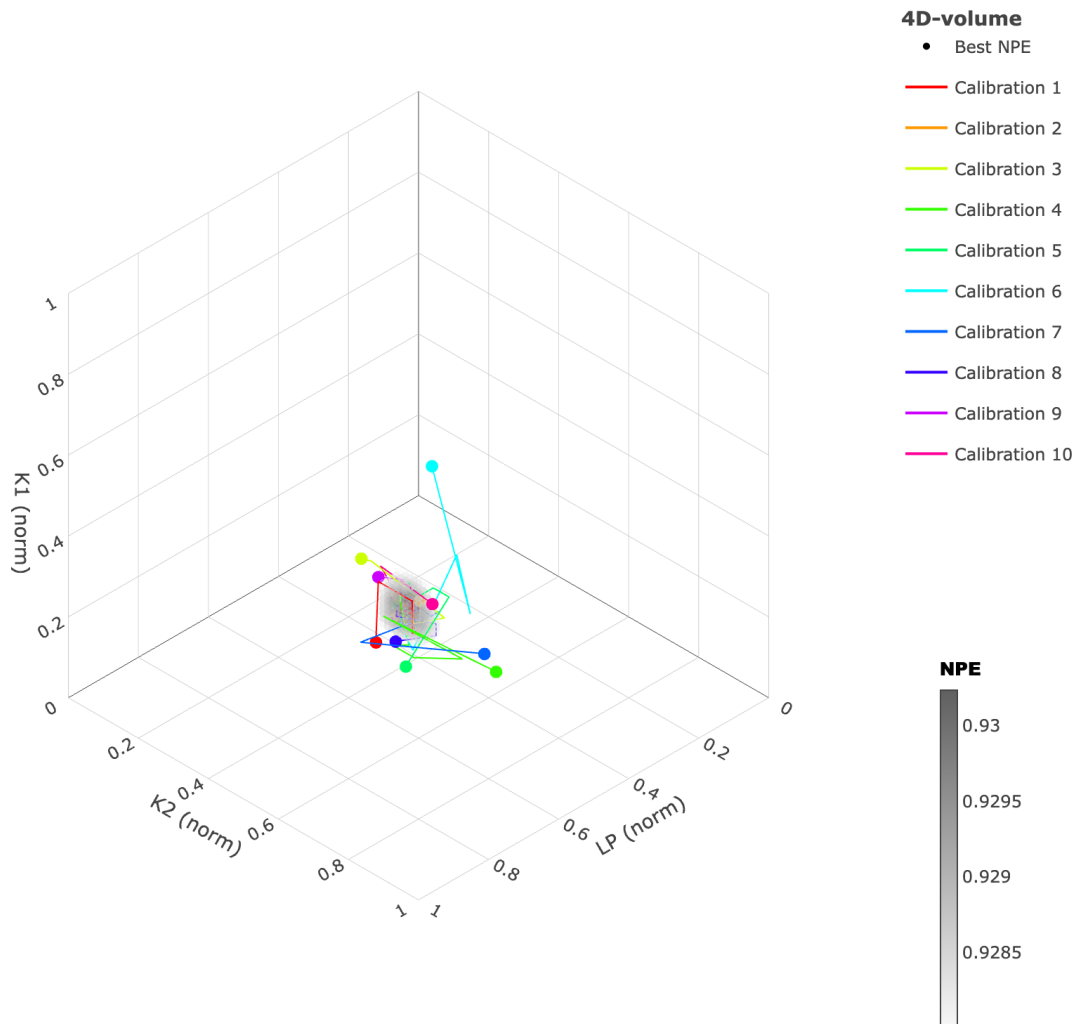
FR000730_4D_E: Persistence Diagram, top 5%



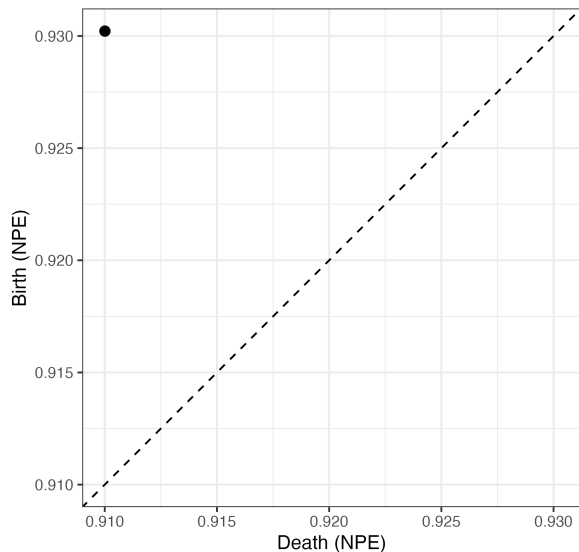
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.93004697	0.93080737	0.93087209	0.9309336	0.93099638
2	0.93063259	0.93098469	0.93100386	0.93100601	0.93099638
3	0.93055678	0.93093535	0.9309634	0.93101036	0.93099638
4	0.93043898	0.93094149	0.93094481	0.93096517	0.93099638
5	0.93056502	0.93067356	0.93076174	0.93083105	0.93099638
6	0.93049153	0.9309526	0.93096183	0.93096183	0.93099638
7	0.93056488	0.93086586	0.93087556	0.9308879	0.93099638
8	0.93089318	0.93093081	0.93094196	0.93099499	0.93099638
9	0.93041507	0.93067907	0.93079386	0.93099836	0.93099638
10	0.93072862	0.93083974	0.93092645	0.93092761	0.93099638

FR000730_4D_J, K2_LP_K1_SFCF

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



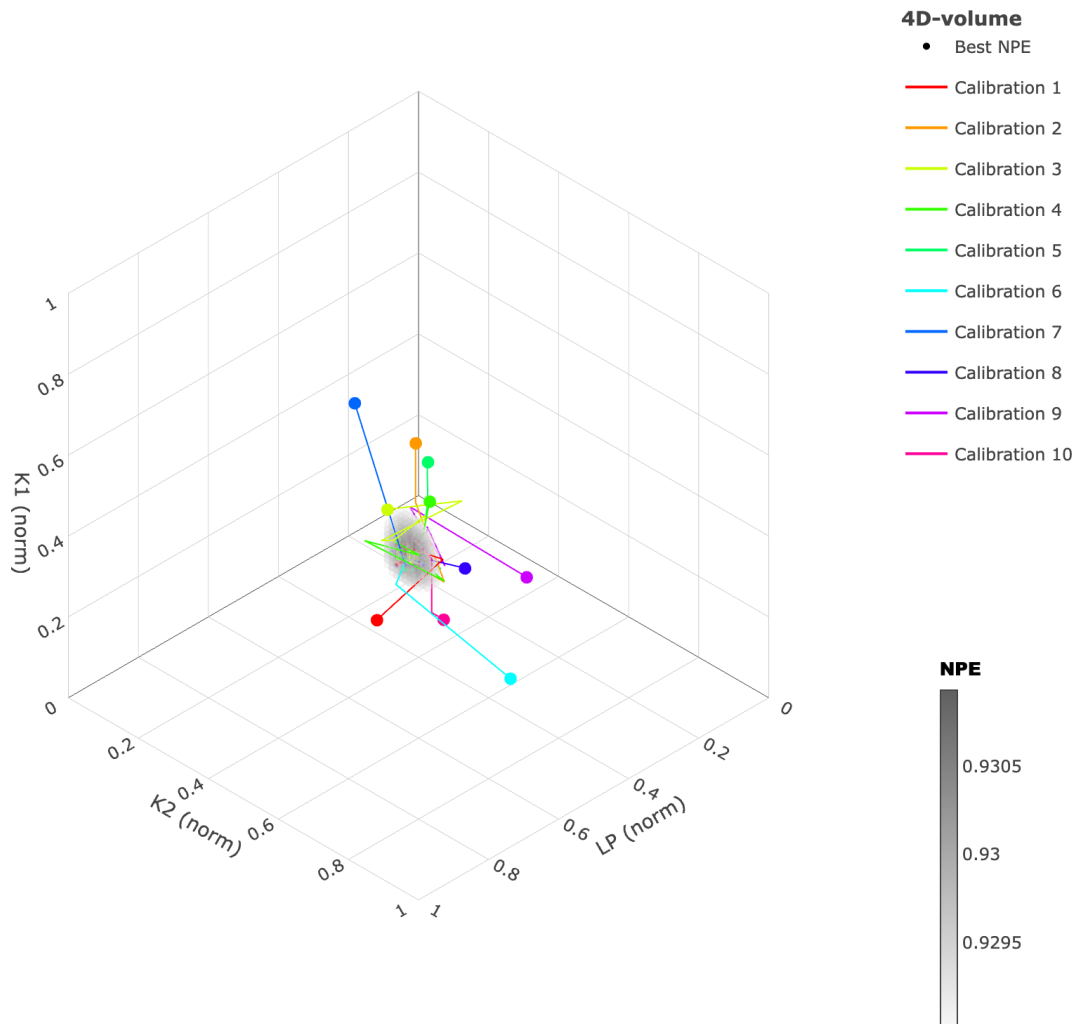
FR000730_4D_J: Persistence Diagram, top 5%



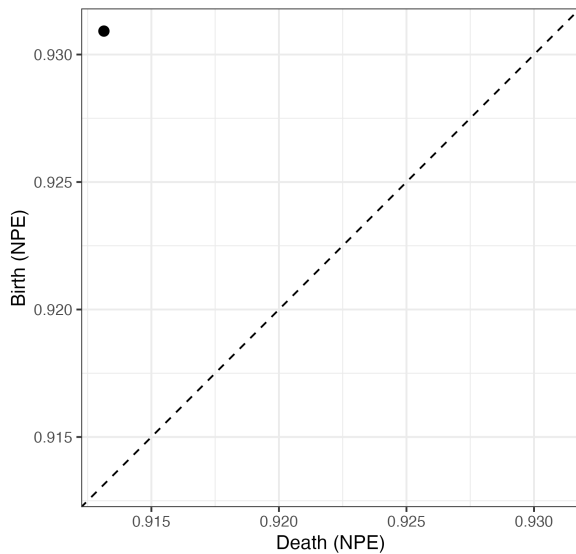
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.92984729	0.93022235	0.93024637	0.93028131	0.93023349
2	0.93010898	0.93023123	0.93025641	0.93027513	0.93023349
3	0.93007784	0.93021067	0.93027349	0.93028146	0.93023349
4	0.930062	0.9302919	0.93029401	0.93030024	0.93023349
5	0.93000381	0.93019561	0.93023844	0.93029413	0.93023349
6	0.9299794	0.93026055	0.93028102	0.93029646	0.93023349
7	0.93021274	0.93028391	0.93030062	0.93030074	0.93023349
8	0.93010623	0.93025597	0.93026694	0.9302866	0.93023349
9	0.9301605	0.93026969	0.93027573	0.93029033	0.93023349
10	0.93000345	0.93028777	0.93028993	0.93029661	0.93023349

FR000730_4D_K, K2_LP_K1_SFCF

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



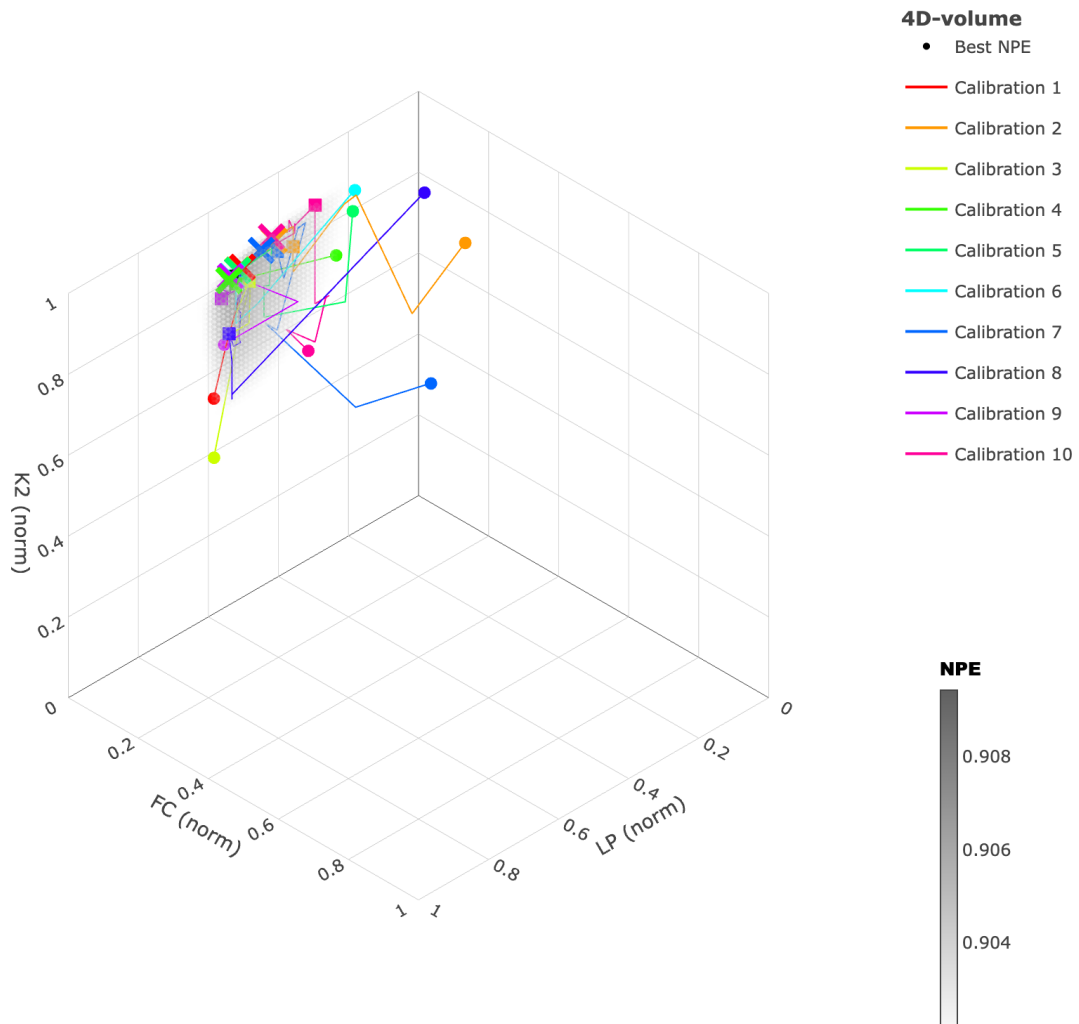
FR000730_4D_K: Persistence Diagram, top 5%



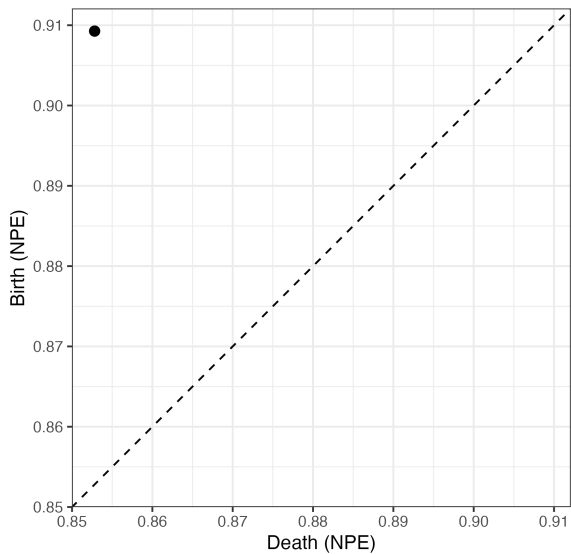
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.93084739	0.93089825	0.93090903	0.93095905	0.930927
2	0.93086531	0.93091657	0.93094923	0.93095616	0.930927
3	0.93073374	0.93091683	0.93092692	0.93095649	0.930927
4	0.93072043	0.93093882	0.93095355	0.9309555	0.930927
5	0.93074829	0.93093258	0.93093513	0.93094802	0.930927
6	0.93086536	0.93093678	0.93095146	0.93095664	0.930927
7	0.93086402	0.93091469	0.93091774	0.93094842	0.930927
8	0.93080866	0.93093664	0.93093815	0.93095645	0.930927
9	0.93073086	0.93093292	0.93095372	0.93095465	0.930927
10	0.93068795	0.93091386	0.93092158	0.93095581	0.930927

FR001413_4D_A, FC_LP_K2_BETA

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



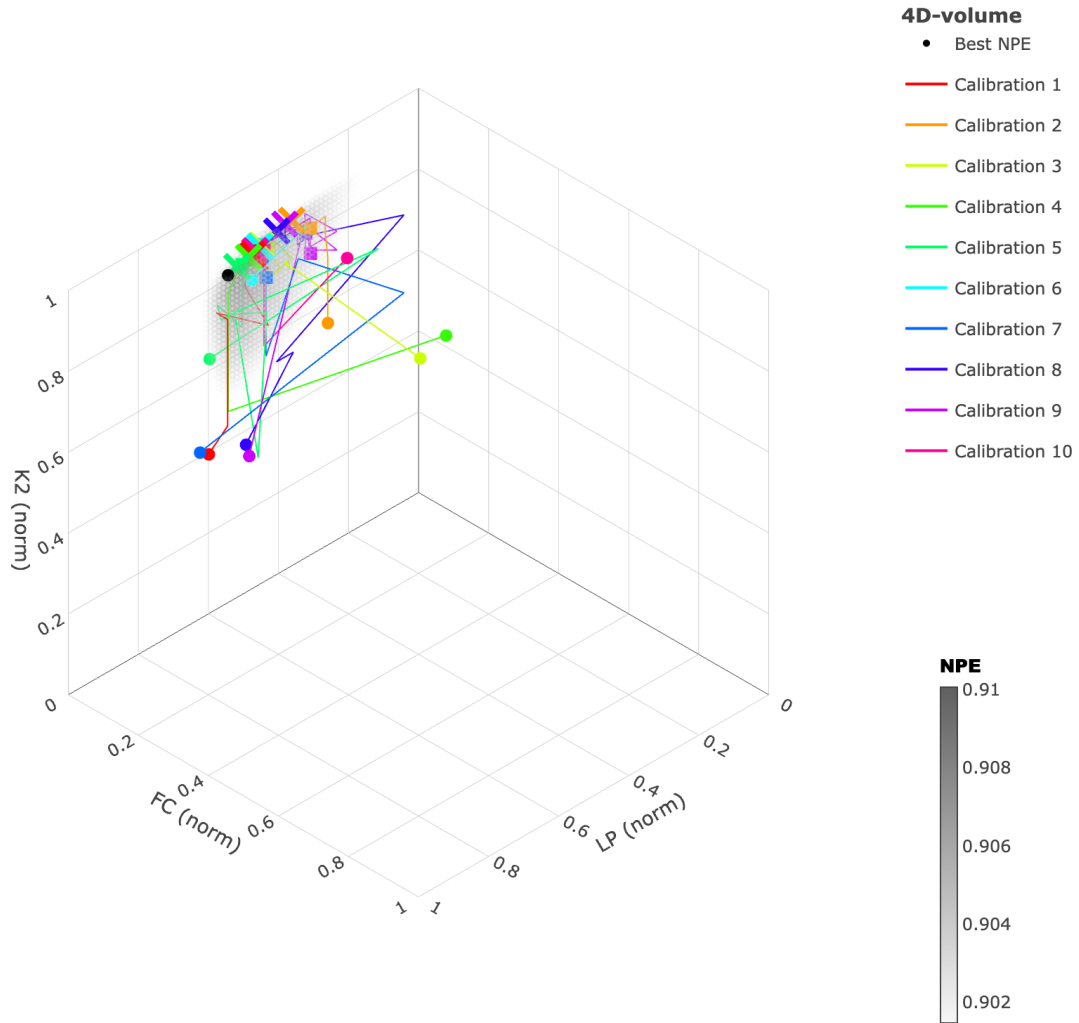
FR001413_4D_A: Persistence Diagram, top 5%



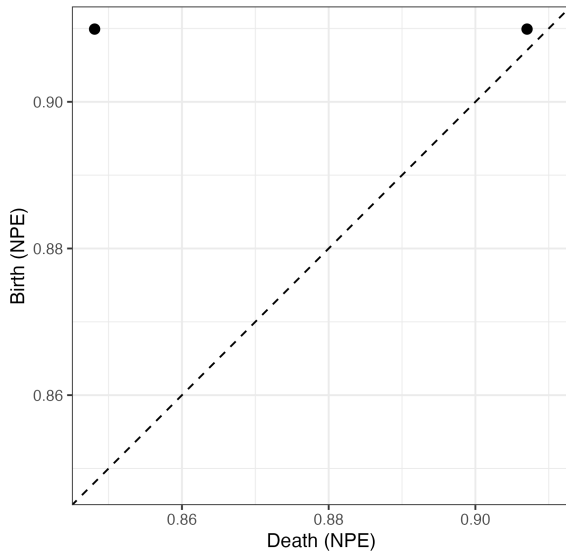
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.90906481	0.90931303	0.90932286	0.90935355	0.90941444
2	0.90655861	0.90688867	0.90726965	0.90800042	0.90941444
3	0.9079689	0.90897302	0.90905838	0.909343	0.90941444
4	0.90851055	0.90893837	0.90908801	0.90930108	0.90941444
5	0.90903925	0.90938034	0.90939543	0.90940365	0.90941444
6	0.90882759	0.90906393	0.90935217	0.90942605	0.90941444
7	0.90780264	0.90801451	0.90854361	0.90873797	0.90941444
8	0.90441325	0.90933908	0.90936758	0.90938019	0.90941444
9	0.9080173	0.90925342	0.90942781	0.90942996	0.90941444
10	0.90459668	0.90660674	0.90743672	0.90744989	0.90941444

FR001413_4D_B, FC_LP_K2_BETA

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
 circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



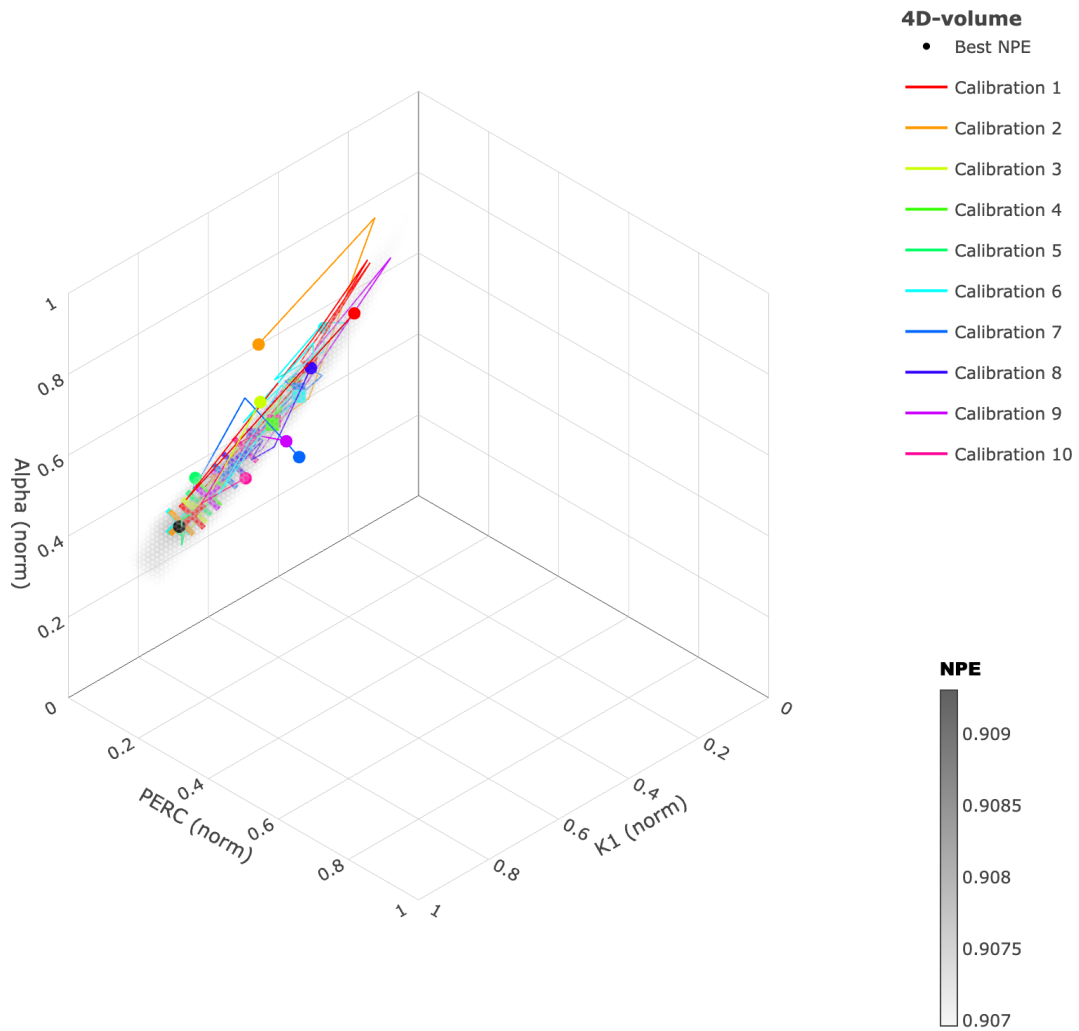
FR001413_4D_B: Persistence Diagram, top 5%



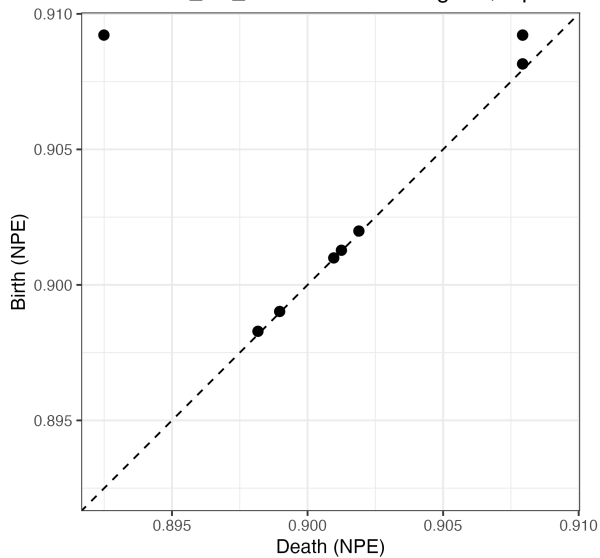
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.90879606	0.90954234	0.90954234	0.90969344	0.91005977
2	0.9056142	0.9068329	0.90726242	0.90764191	0.91005977
3	0.90810885	0.90905394	0.90918628	0.90930578	0.91005977
4	0.90952864	0.90962902	0.90985735	0.90988894	0.91005977
5	0.9099061	0.91000635	0.91003183	0.91003183	0.91005977
6	0.90818306	0.90917242	0.90927194	0.90942699	0.91005977
7	0.90742066	0.90776461	0.9091426	0.90942749	0.91005977
8	0.90164061	0.90614336	0.90680393	0.9083782	0.91005977
9	0.90501529	0.90620118	0.90775869	0.90776434	0.91005977
10	0.90736341	0.90933493	0.90950738	0.90960043	0.91005977

FR001413_4D_D, PERC_K1_Alpha_MAXBAS

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



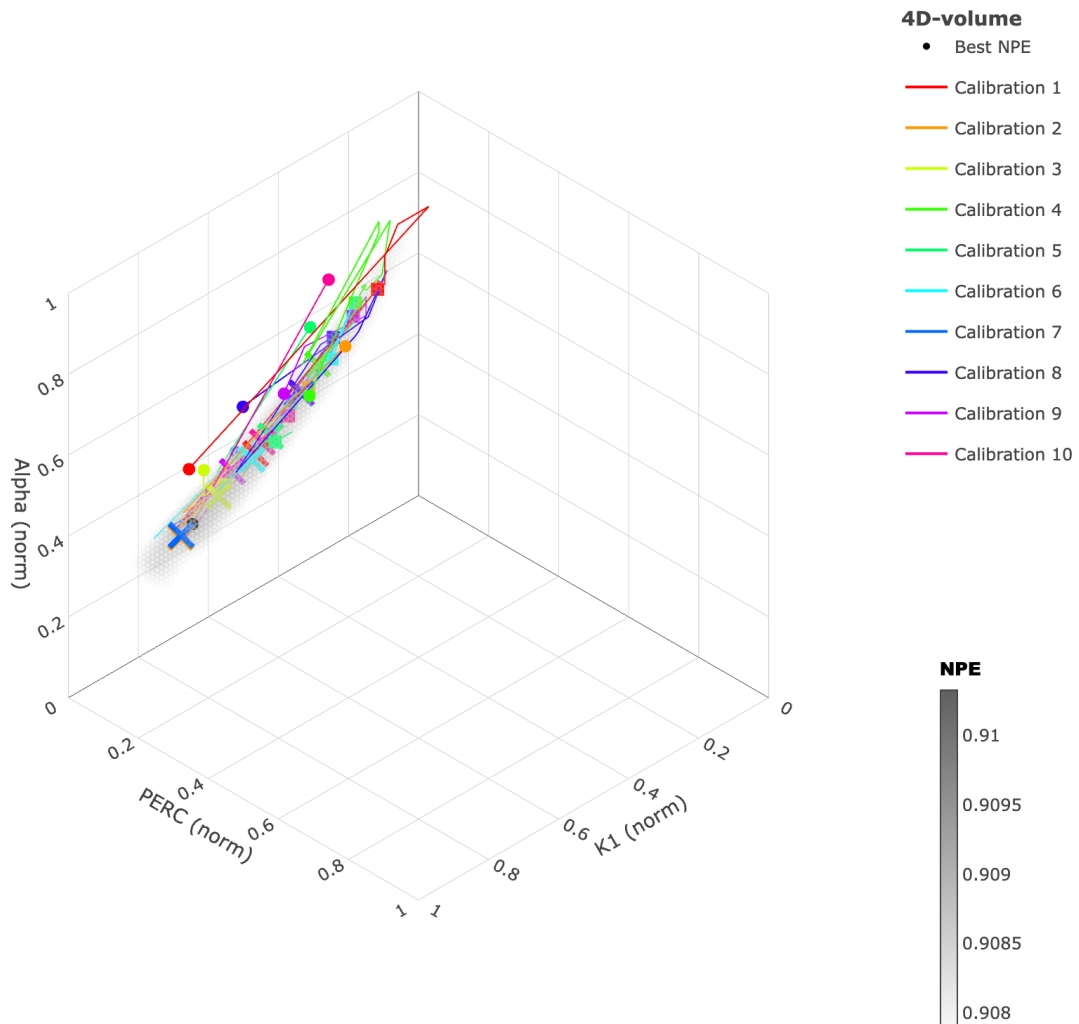
FR001413_4D_D: Persistence Diagram, top 5%



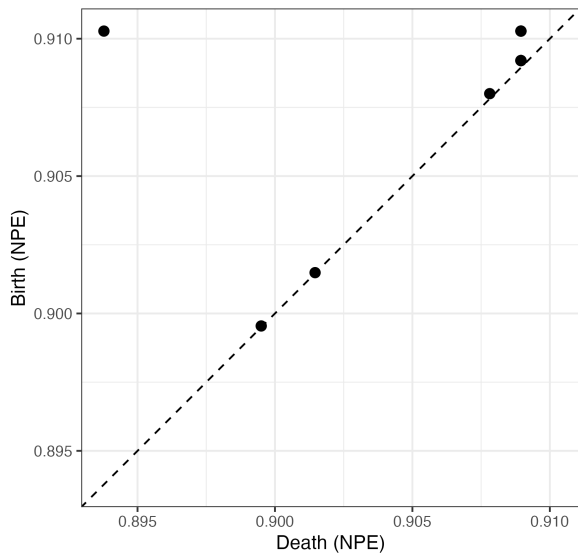
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.90795243	0.90814534	0.9085536	0.90927581	0.90930567
2	0.90819472	0.90903137	0.90923197	0.909362	0.90930567
3	0.90812517	0.90882062	0.90908051	0.90931876	0.90930567
4	0.90846119	0.90885753	0.90906417	0.90924042	0.90930567
5	0.90850941	0.90927392	0.90927953	0.90928149	0.90930567
6	0.90838067	0.90908907	0.90912761	0.90913571	0.90930567
7	0.9084789	0.90905933	0.90915442	0.90919609	0.90930567
8	0.90829704	0.90912892	0.90912892	0.90916412	0.90930567
9	0.90864855	0.90920398	0.90927369	0.90927369	0.90930567
10	0.90882572	0.90890074	0.90895272	0.90908203	0.90930567

FR001413_4D_E, PERC_K1_Alpha_MAXBAS

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



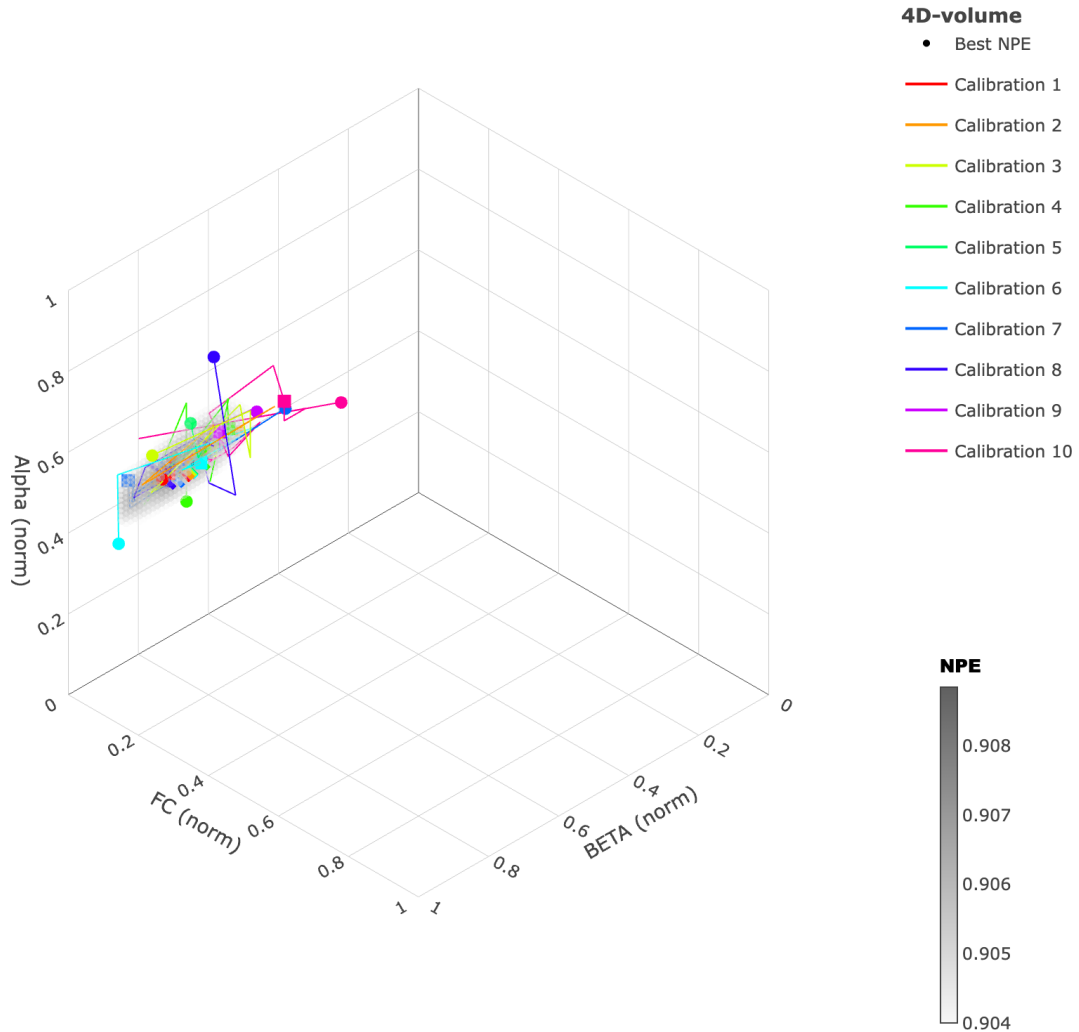
FR001413_4D_E: Persistence Diagram, top 5%



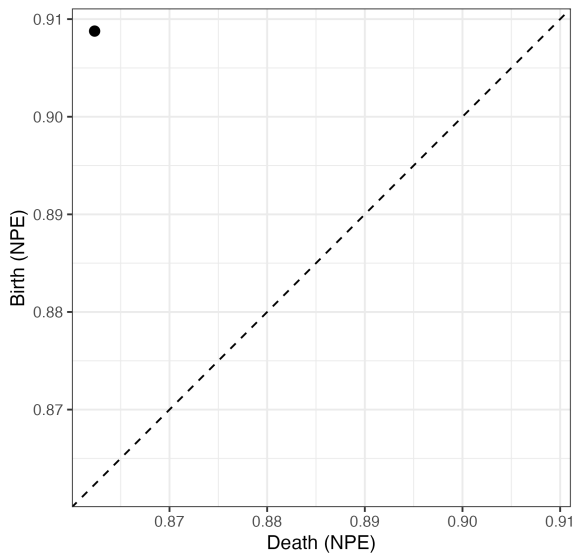
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.90913387	0.90959599	0.91002982	0.91011392	0.9103261
2	0.90942628	0.91010846	0.91030604	0.91032639	0.9103261
3	0.91015234	0.91026995	0.91026995	0.91030866	0.9103261
4	0.90871739	0.90894926	0.90938125	0.90958502	0.9103261
5	0.90932835	0.91004817	0.91004817	0.91008453	0.9103261
6	0.90957322	0.91006982	0.91006982	0.91021445	0.9103261
7	0.90922712	0.91026659	0.91031898	0.91034132	0.9103261
8	0.90864337	0.90975794	0.90988703	0.90990827	0.9103261
9	0.90937064	0.90957246	0.90998442	0.91008925	0.9103261
10	0.90928276	0.91001207	0.91001961	0.91006985	0.9103261

FR001413_4D_J, FC_BETA_Alpha_TT

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



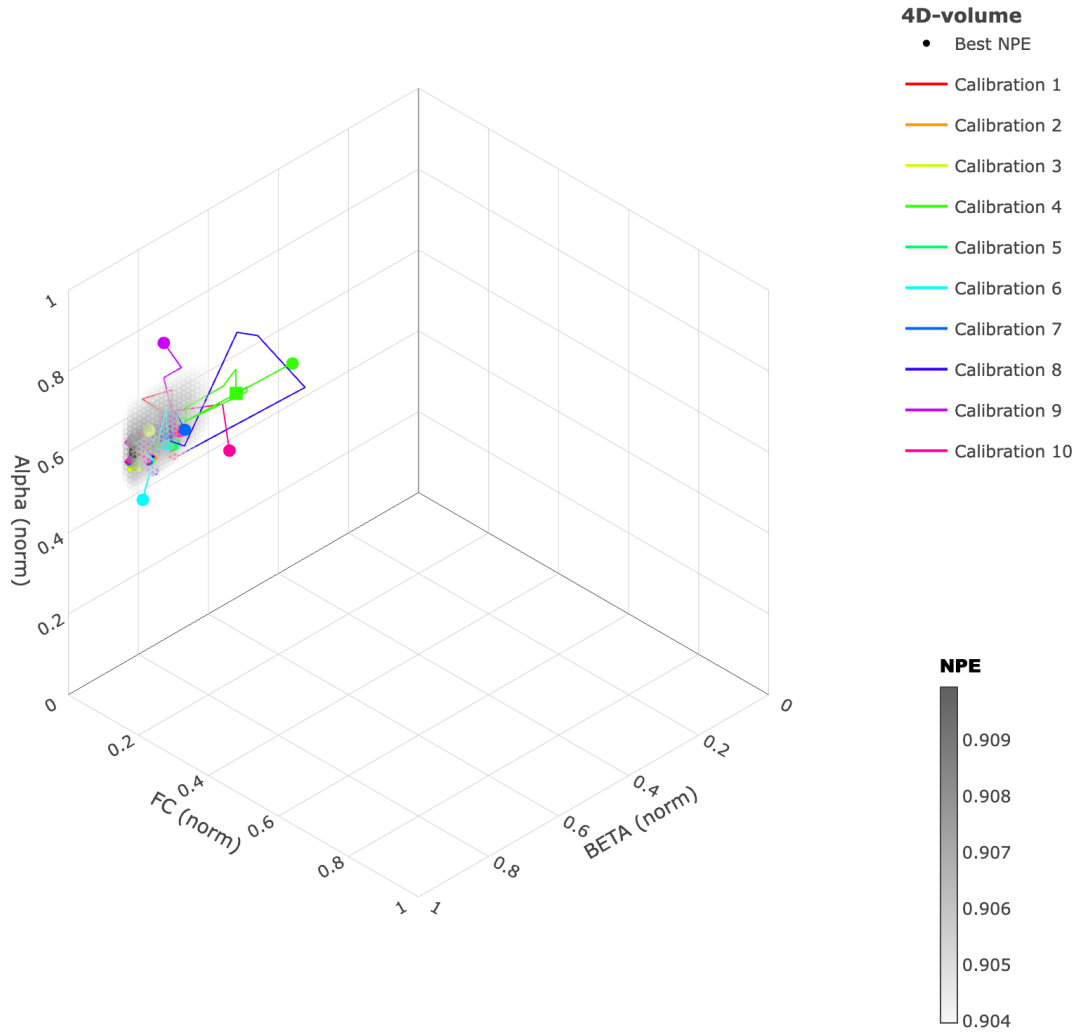
FR001413_4D_J: Persistence Diagram, top 5%



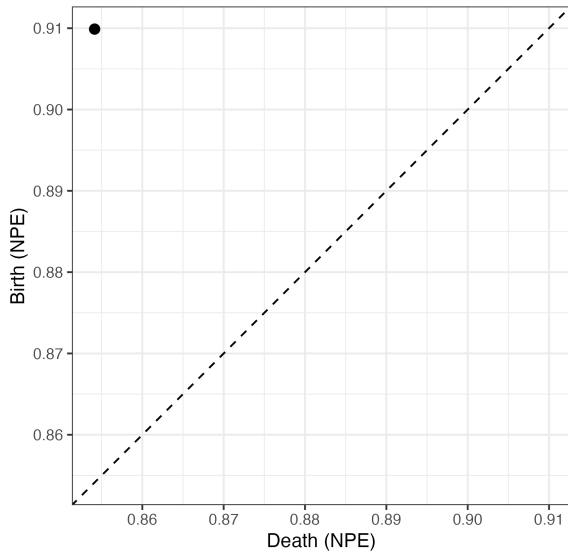
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.90875524	0.90894742	0.9090093	0.9090093	0.90883933
2	0.90825569	0.90848402	0.90892156	0.90898839	0.90883933
3	0.90793551	0.90877932	0.90890153	0.90895089	0.90883933
4	0.90615075	0.90758356	0.90847335	0.90847374	0.90883933
5	0.90868936	0.90889154	0.90894429	0.90895717	0.90883933
6	0.90586508	0.90861001	0.90862208	0.90885833	0.90883933
7	0.90514483	0.90812183	0.90889302	0.90894572	0.90883933
8	0.90838416	0.9086116	0.90866556	0.90879921	0.90883933
9	0.90616341	0.90856594	0.90876035	0.9089899	0.90883933
10	0.89380834	0.90804108	0.90877655	0.90896848	0.90883933

FR001413_4D_K, FC_BETA_Alpha_TT

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



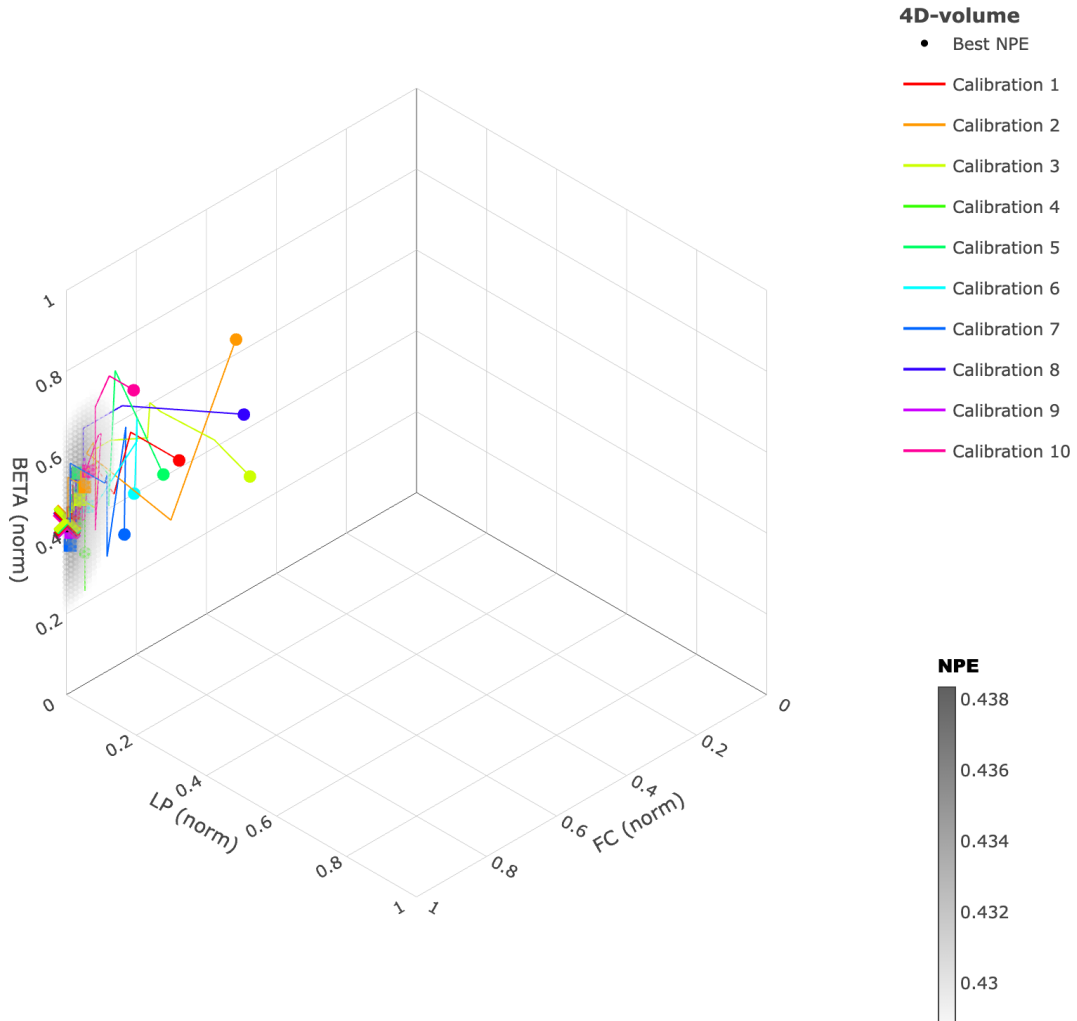
FR001413_4D_K: Persistence Diagram, top 5%



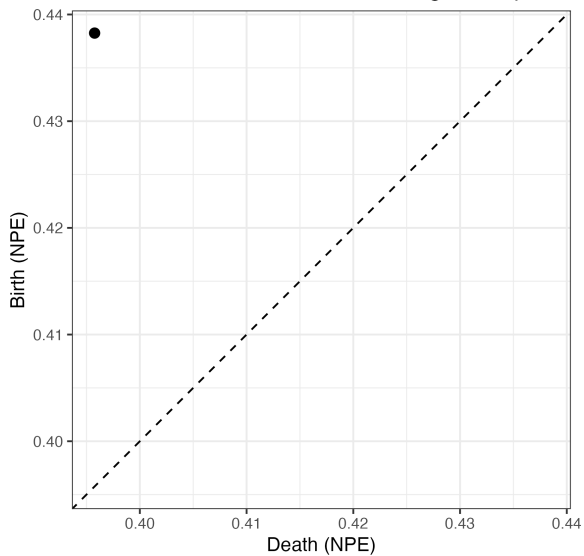
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.90804791	0.90956715	0.90991993	0.9100211	0.90994186
2	0.90956468	0.90984569	0.91001772	0.91002726	0.90994186
3	0.90927266	0.90965642	0.90969042	0.91004326	0.90994186
4	0.89693266	0.90785742	0.90893124	0.90997147	0.90994186
5	0.90769562	0.90994639	0.910007	0.91001816	0.90994186
6	0.90846021	0.9099421	0.90999973	0.91001107	0.90994186
7	0.90916694	0.909648	0.90967243	0.91000662	0.90994186
8	0.90902462	0.90908867	0.90924685	0.9100155	0.90994186
9	0.90811232	0.90996862	0.91000949	0.91002349	0.90994186
10	0.90751898	0.90990576	0.90994651	0.91002859	0.90994186

GB000296_4D_A, LP_FC_BETA_PERC

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



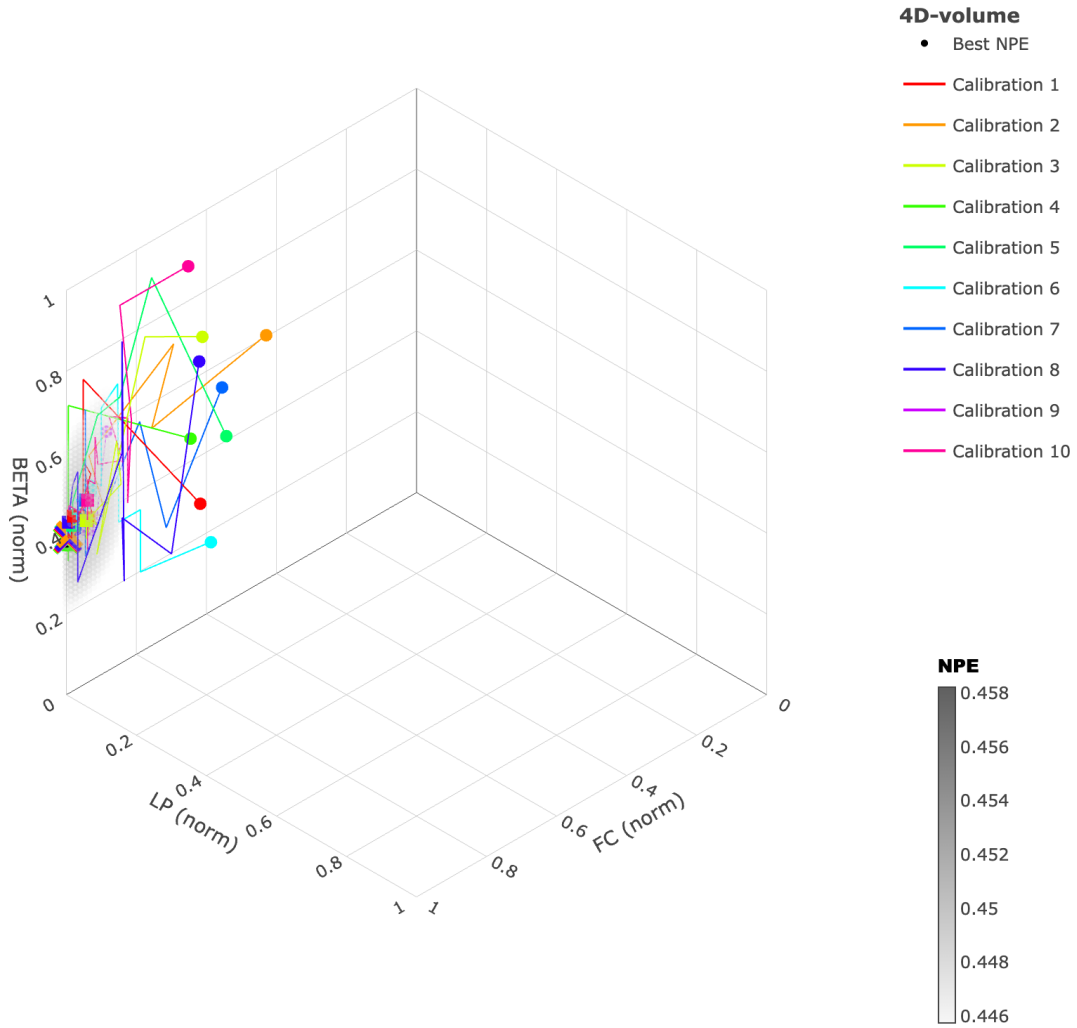
GB000296_4D_A: Persistence Diagram, top 5%



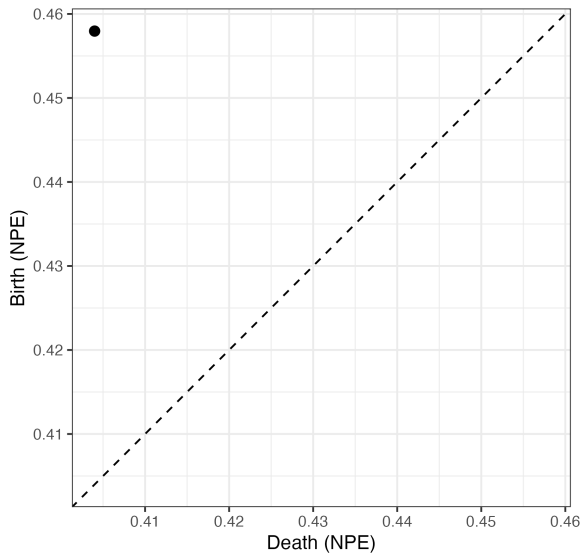
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.43725401	0.43804158	0.43804238	0.43818621	0.43833831
2	0.43508775	0.43805529	0.4380712	0.43808601	0.43833831
3	0.4359567	0.43678211	0.43709087	0.43820366	0.43833831
4	0.43625458	0.43766163	0.43780318	0.43813979	0.43833831
5	0.43540492	0.43719876	0.43771287	0.4380322	0.43833831
6	0.434645	0.43626613	0.43710435	0.43811313	0.43833831
7	0.43664212	0.43774506	0.43784393	0.43810833	0.43833831
8	0.43590095	0.43773629	0.43794895	0.4382697	0.43833831
9	0.43721938	0.43760008	0.4380272	0.43816687	0.43833831
10	0.4343102	0.43813924	0.4382863	0.43830795	0.43833831

GB000296_4D_B, LP_FC_BETA_PERC

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



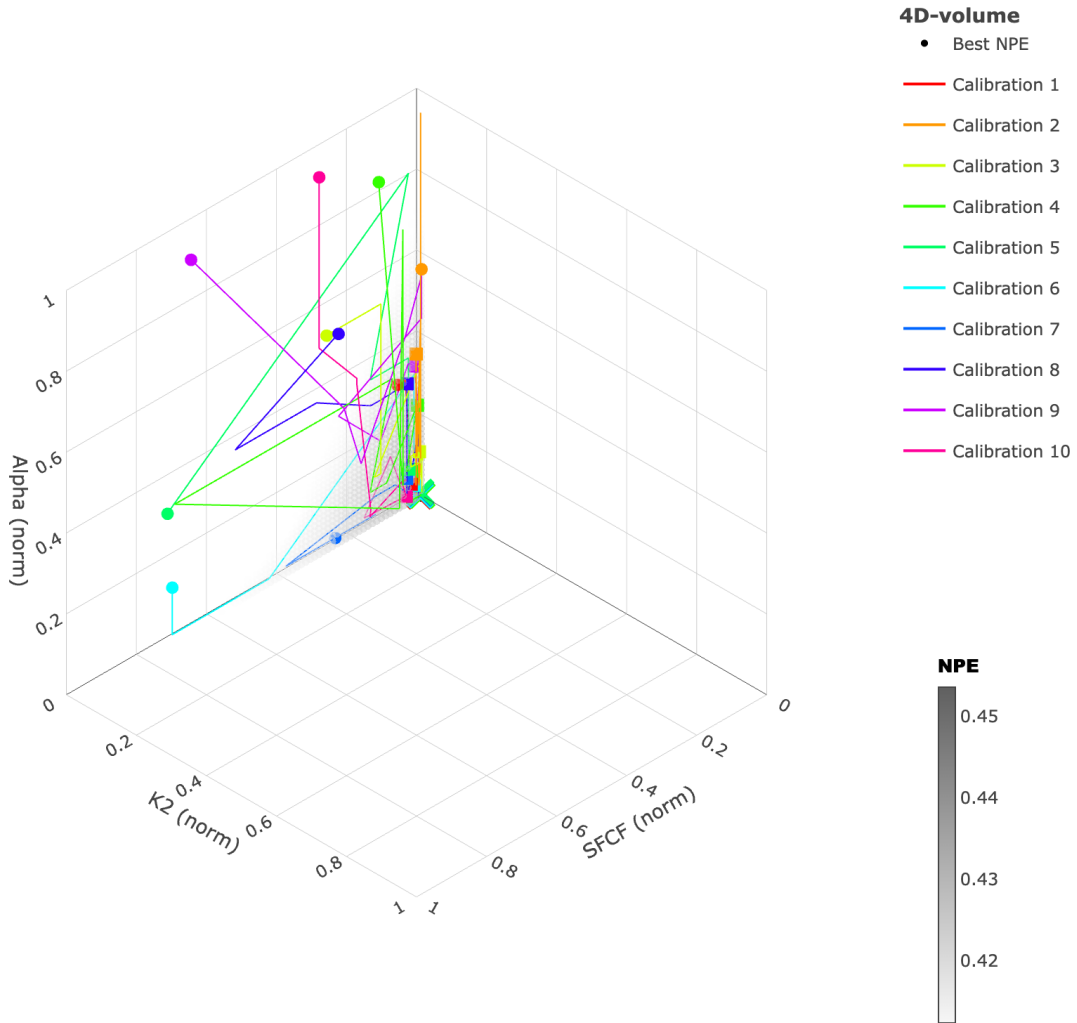
GB000296_4D_B: Persistence Diagram, top 5%



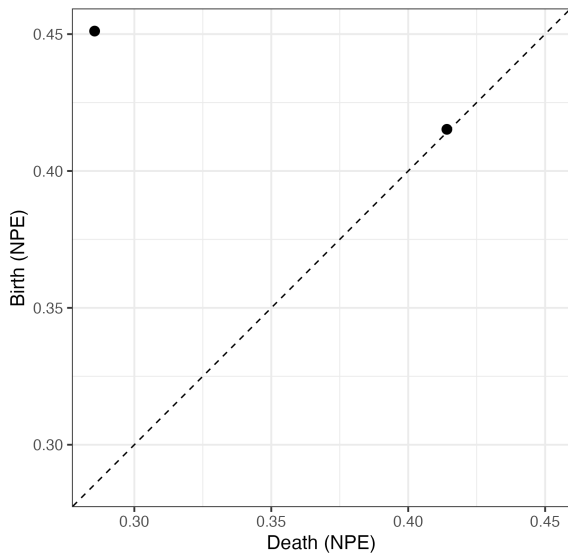
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.4565561	0.45751588	0.45792551	0.458073	0.4582199
2	0.4543155	0.45672471	0.45728371	0.45775035	0.4582199
3	0.45482337	0.45806696	0.45806895	0.45806895	0.4582199
4	0.45781913	0.45815516	0.45815516	0.4582132	0.4582199
5	0.45456525	0.45735956	0.4577956	0.45798586	0.4582199
6	0.45332865	0.45703152	0.45753727	0.45795171	0.4582199
7	0.45479469	0.4559109	0.45780774	0.45809424	0.4582199
8	0.45537349	0.45792554	0.45793291	0.45797508	0.4582199
9	0.45423773	0.4574264	0.45792505	0.45792505	0.4582199
10	0.45395563	0.45787509	0.45794247	0.45803065	0.4582199

GB000296_4D_D, K2_SFCF_Alpha_TT

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



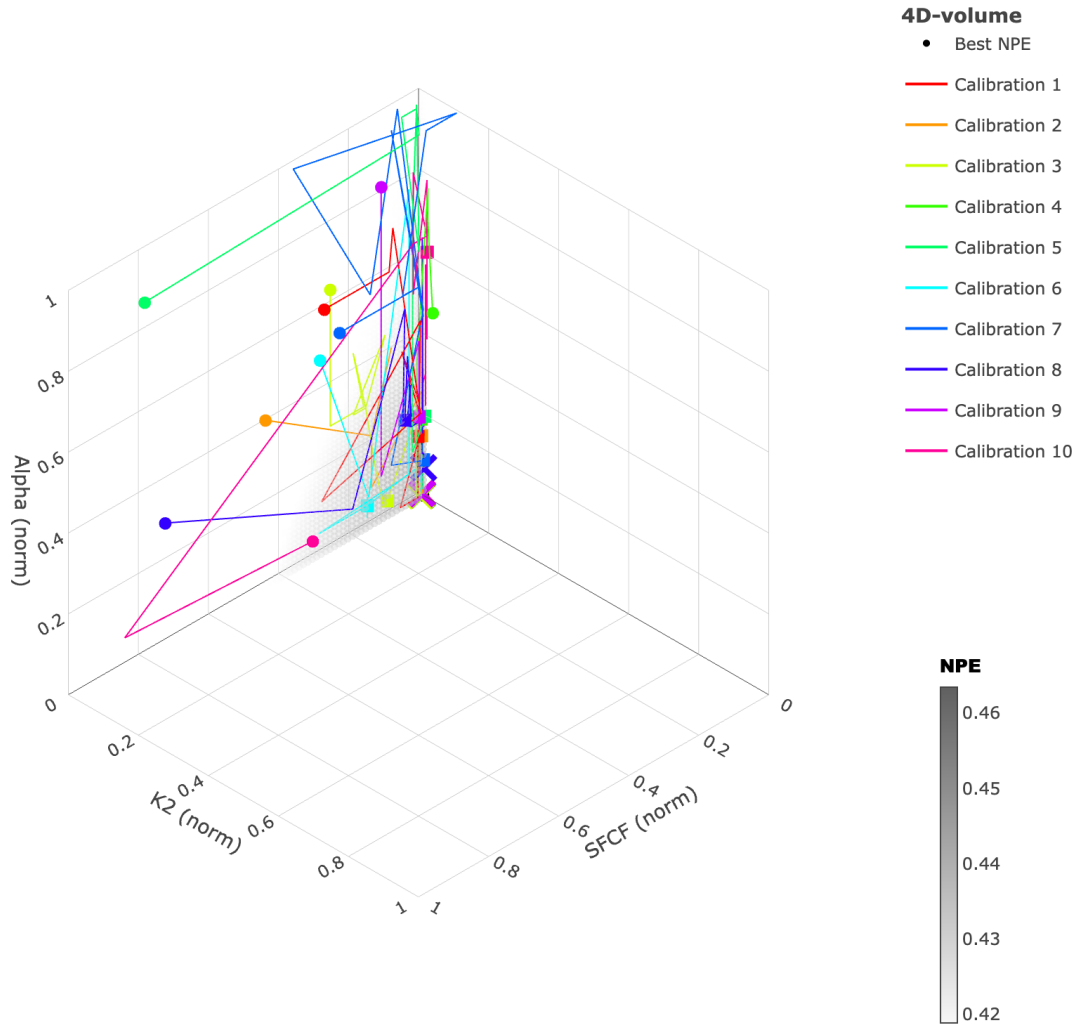
GB000296_4D_D: Persistence Diagram, top 5%



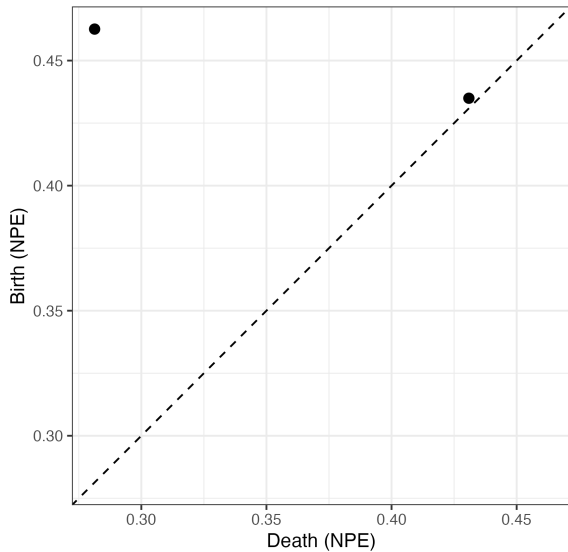
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.44439329	0.45289166	0.45290025	0.45298305	0.45351275
2	0.39942228	0.43699068	0.44163608	0.45334938	0.45351275
3	0.40572101	0.42079602	0.45317916	0.45317916	0.45351275
4	0.42473016	0.43102844	0.43856965	0.43997223	0.45351275
5	0.44016245	0.44611905	0.45270337	0.4534764	0.45351275
6	0.44784228	0.44953717	0.45188367	0.45330539	0.45351275
7	0.44616925	0.45346467	0.45346467	0.45348645	0.45351275
8	0.42582851	0.43515342	0.44573762	0.44789927	0.45351275
9	0.4279378	0.44888946	0.45310042	0.4533716	0.45351275
10	0.42417725	0.44766853	0.44940819	0.45071456	0.45351275

GB000296_4D_E, K2_SFCE_Alpha_TT

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



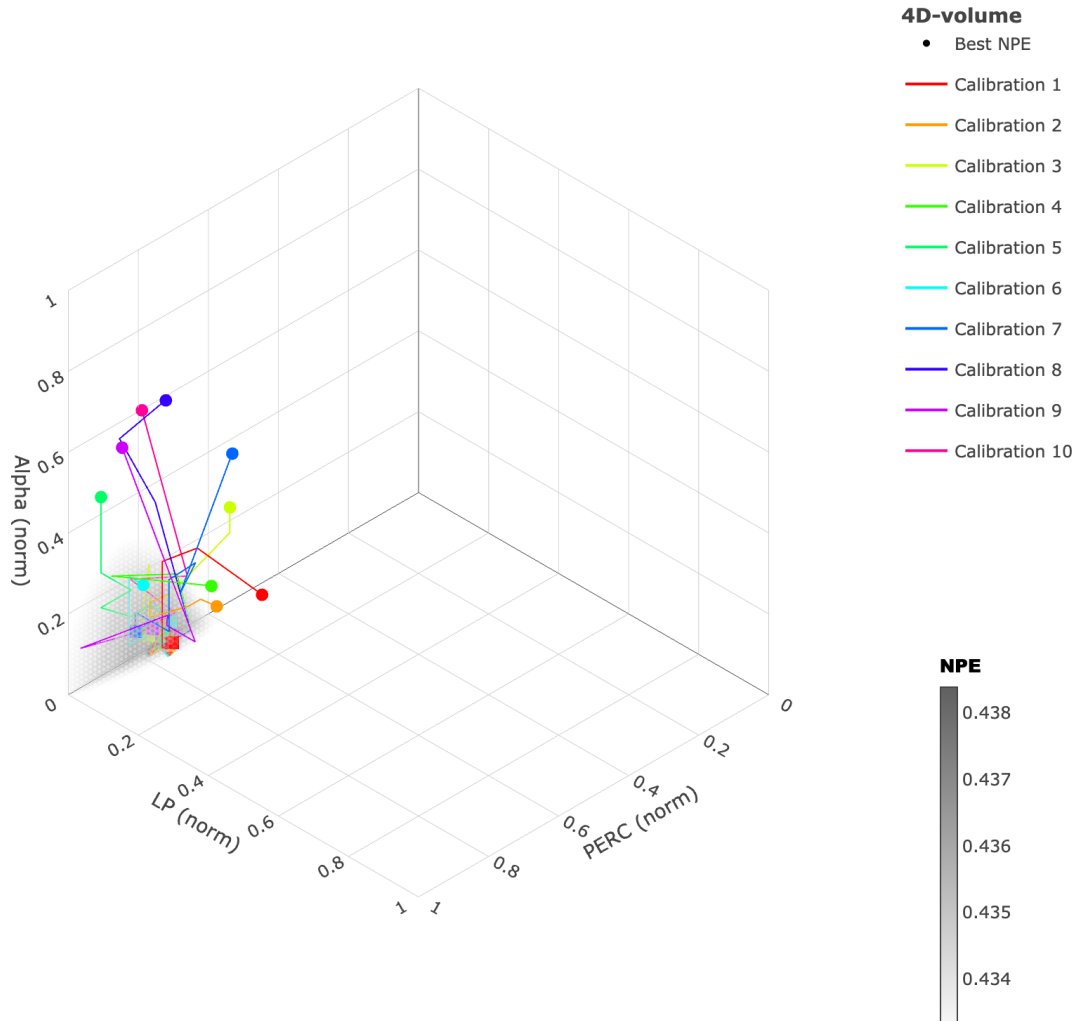
GB000296_4D_E: Persistence Diagram, top 5%



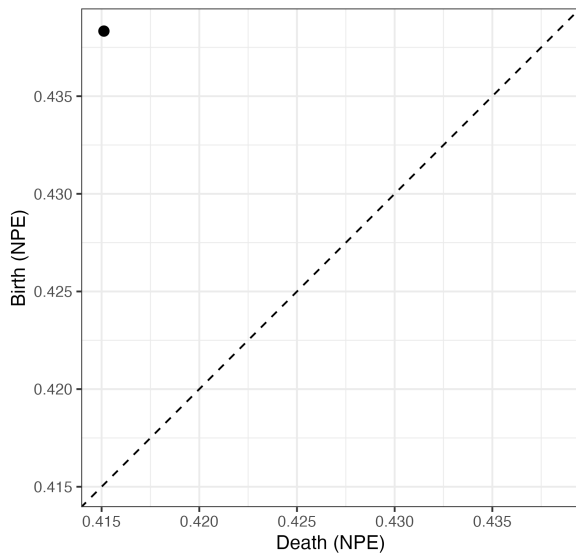
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.4552748	0.46376585	0.46414638	0.46415892	0.46340818
2	0.45824257	0.46051692	0.46388715	0.46439	0.46340818
3	0.44879774	0.45888159	0.46266323	0.46321602	0.46340818
4	0.45027042	0.46010137	0.46321614	0.46414818	0.46340818
5	0.4291576	0.46182314	0.46264411	0.46301235	0.46340818
6	0.44465524	0.46316102	0.46399705	0.46440428	0.46340818
7	0.44255277	0.46405114	0.4643232	0.46439034	0.46340818
8	0.42468551	0.43013522	0.44958389	0.45288212	0.46340818
9	0.42472907	0.43343857	0.45887511	0.46329386	0.46340818
10	0.39605762	0.41390261	0.46235464	0.46276389	0.46340818

GB000296_4D_J, LP_PERC_Alpha_MAXBAS

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



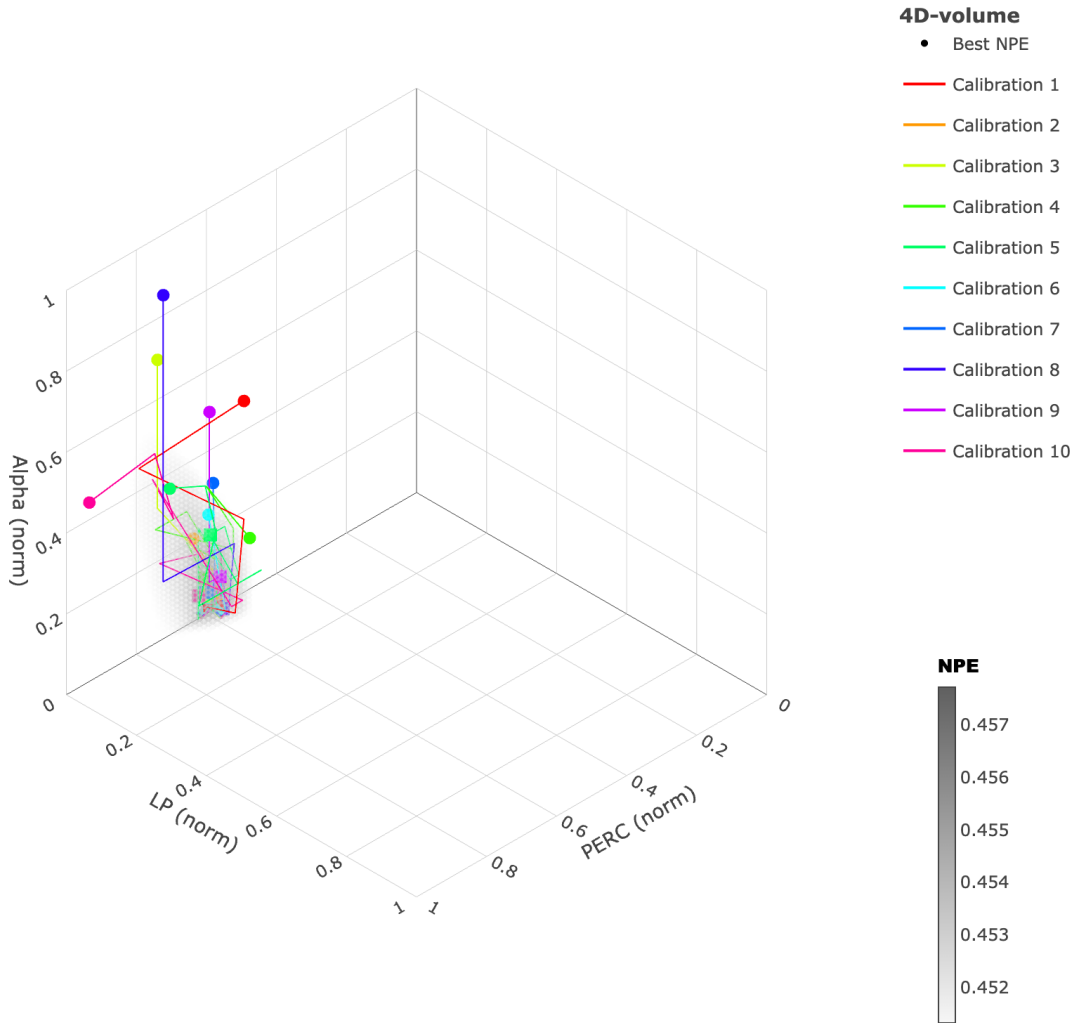
GB000296_4D_J: Persistence Diagram, top 5%



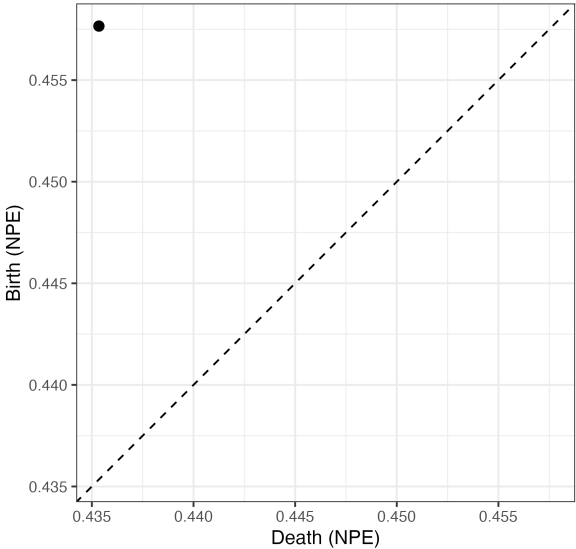
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.43470894	0.43808338	0.43818395	0.43822171	0.43837879
2	0.4362423	0.438233	0.438233	0.43825237	0.43837879
3	0.43757955	0.43799096	0.43814483	0.43819718	0.43837879
4	0.43693376	0.43805009	0.43817677	0.43831286	0.43837879
5	0.43732784	0.43805721	0.43821972	0.43826025	0.43837879
6	0.43713724	0.43814105	0.43822705	0.43830335	0.43837879
7	0.43641888	0.43755565	0.43825294	0.43830131	0.43837879
8	0.43626057	0.43818673	0.43826107	0.43831157	0.43837879
9	0.43714896	0.43778668	0.43823029	0.4383343	0.43837879
10	0.43753945	0.43817443	0.43829981	0.43831079	0.43837879

GB000296_4D_K, LP_PERC_Alpha_MAXBAS

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



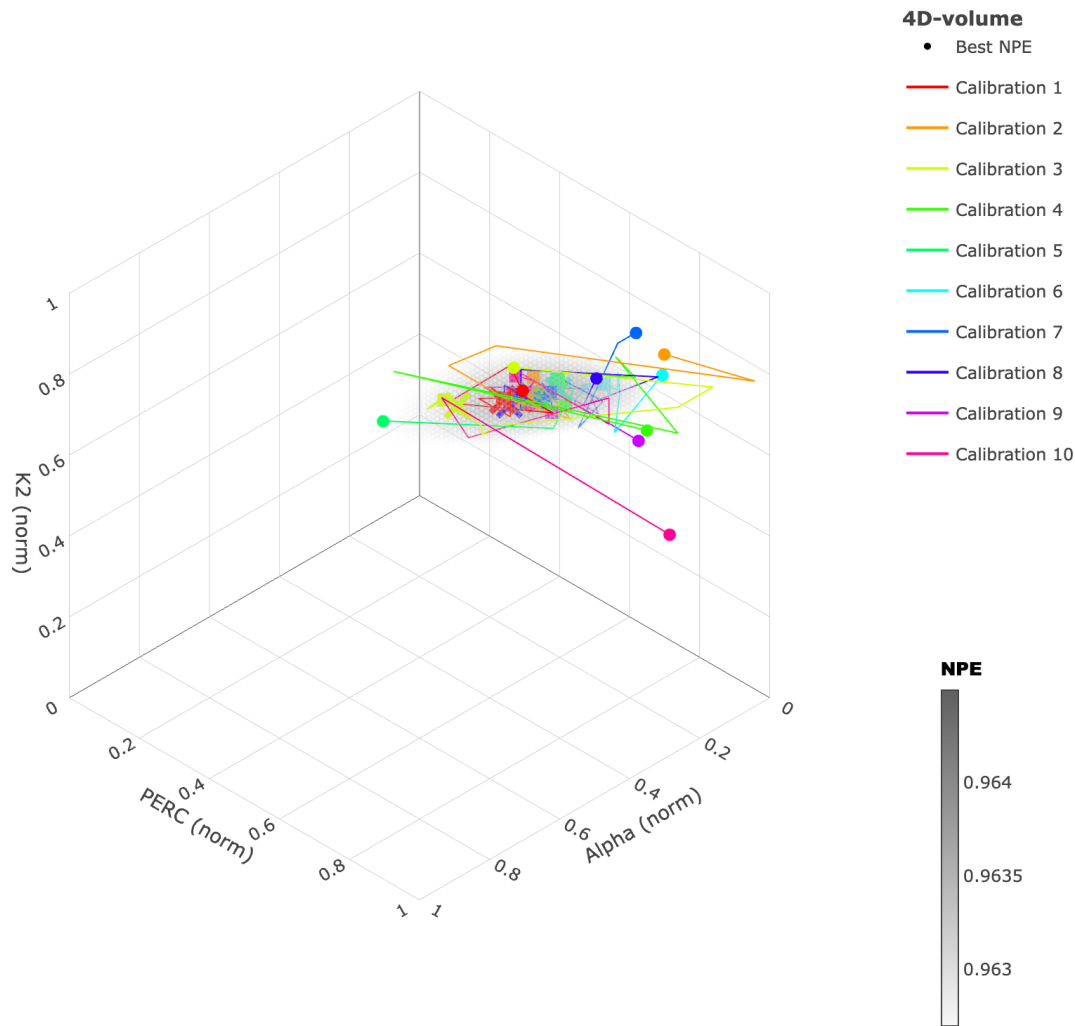
GB000296_4D_K: Persistence Diagram, top 5%



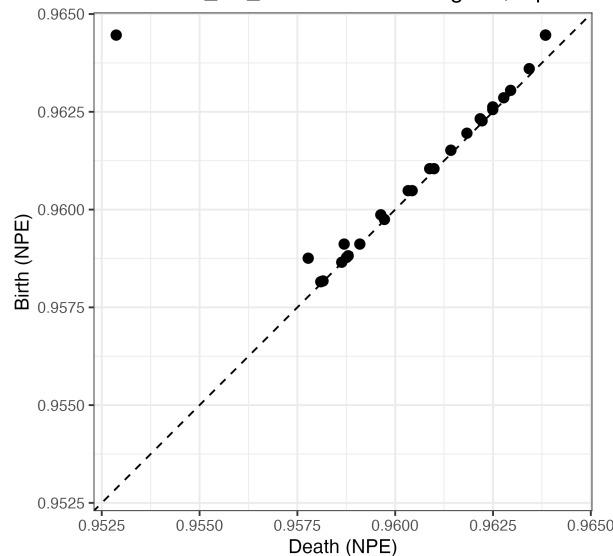
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.45647315	0.45756633	0.45768629	0.45768926	0.45771661
2	0.45667468	0.4575472	0.45755833	0.45760126	0.45771661
3	0.45693197	0.45759903	0.45768334	0.4577779	0.45771661
4	0.45720151	0.45776576	0.45776576	0.45776576	0.45771661
5	0.45231353	0.45671926	0.4576719	0.4577482	0.45771661
6	0.45716277	0.45739633	0.45740506	0.45746822	0.45771661
7	0.45712558	0.45751707	0.45763348	0.45776677	0.45771661
8	0.45581477	0.45729465	0.45734032	0.45754124	0.45771661
9	0.45404842	0.45565679	0.45739896	0.45745461	0.45771661
10	0.45664986	0.45760291	0.4576926	0.45769743	0.45771661

GB000494_4D_A, PERC_Alpha_K2_K1

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



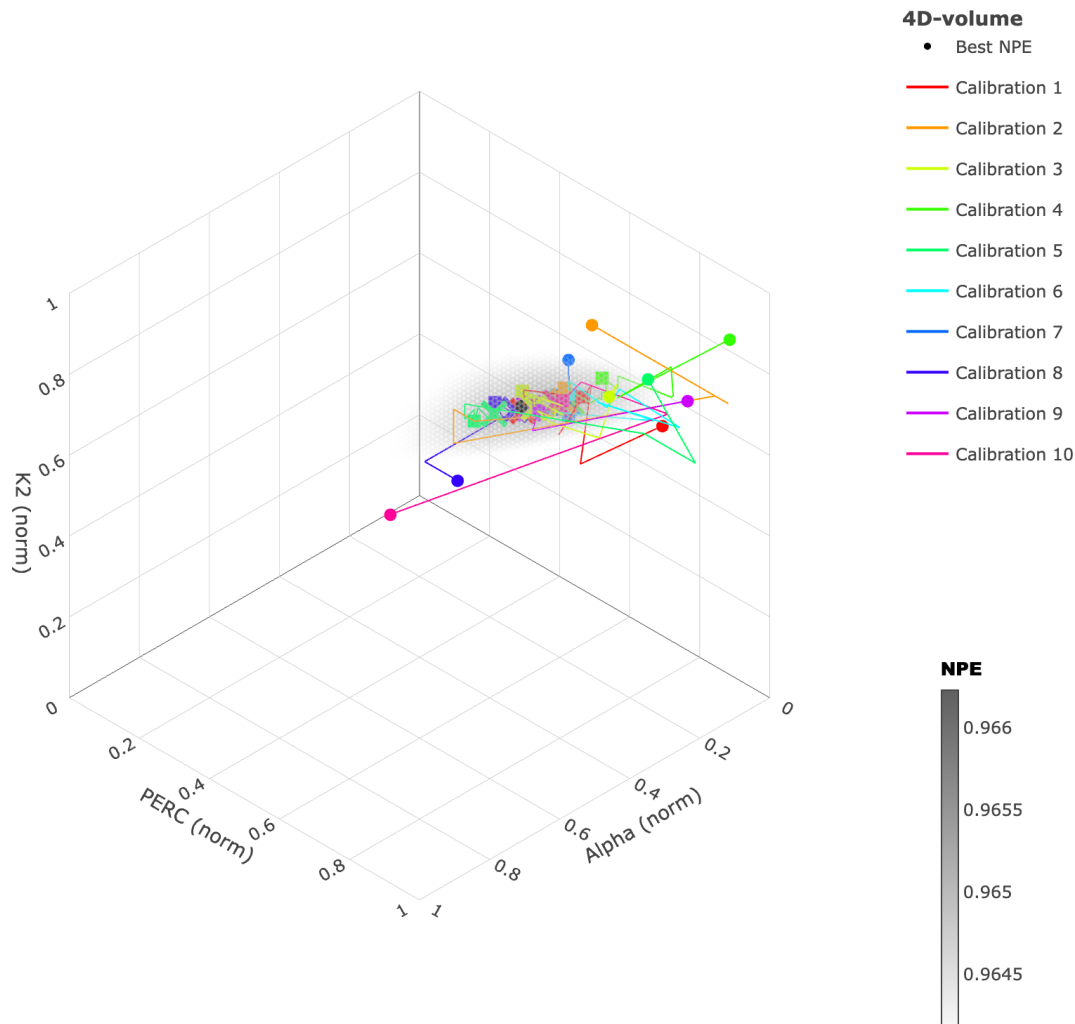
GB000494_4D_A: Persistence Diagram, top 5%



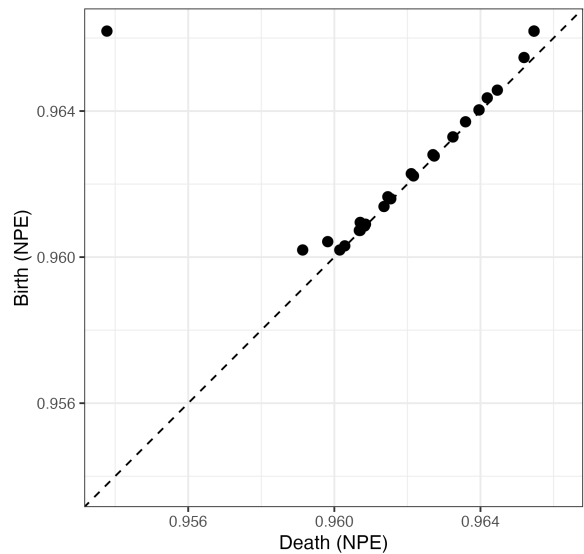
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.96438804	0.96439151	0.96439151	0.9643926	0.96449437
2	0.96401854	0.96444962	0.96447646	0.9644871	0.96449437
3	0.96348271	0.96386231	0.96391566	0.96392939	0.96449437
4	0.96374208	0.96443696	0.96446381	0.9644684	0.96449437
5	0.96400577	0.96428454	0.96434314	0.96439074	0.96449437
6	0.9633015	0.96349898	0.96378086	0.96409022	0.96449437
7	0.96420137	0.96437354	0.96443433	0.96447155	0.96449437
8	0.96380914	0.96440423	0.96441189	0.9644167	0.96449437
9	0.96384406	0.96440287	0.96448418	0.96450567	0.96449437
10	0.96379745	0.96446756	0.96449135	0.96450992	0.96449437

GB000494_4D_B, PERC_Alpha_K2_K1

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



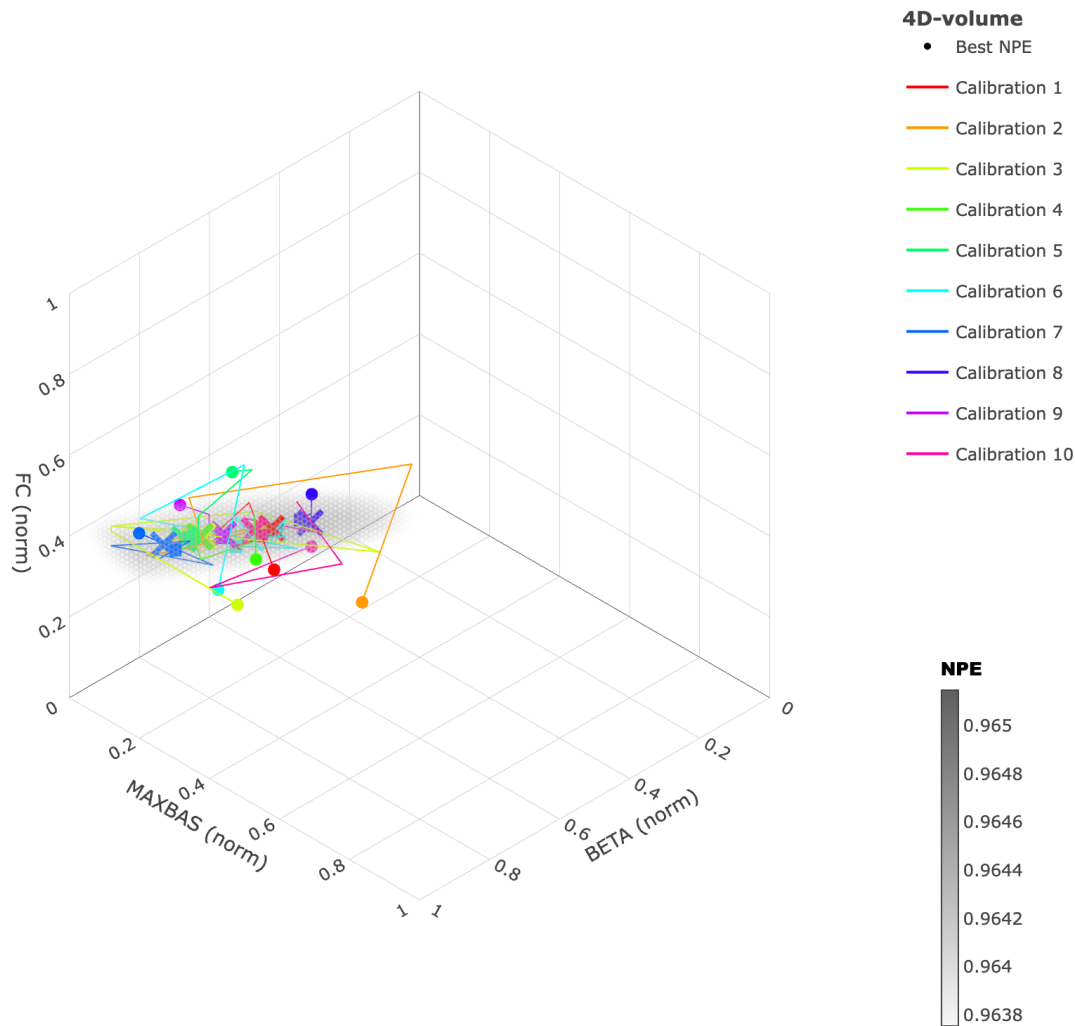
GB000494_4D_B: Persistence Diagram, top 5%



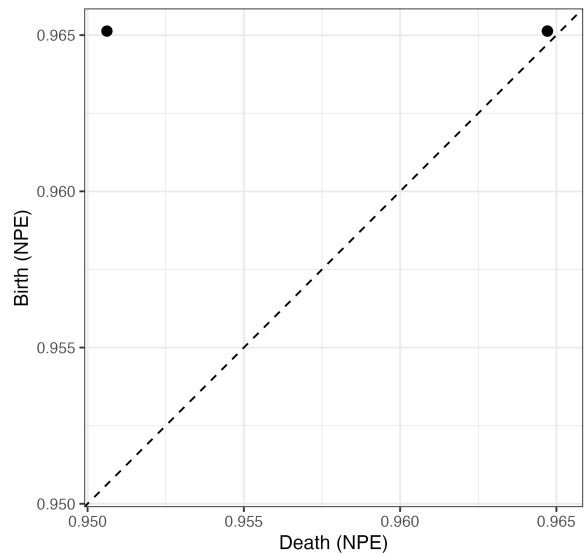
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.96567804	0.96619268	0.96622773	0.96623006	0.96622768
2	0.96579126	0.96596265	0.96597218	0.96597218	0.96622768
3	0.96551983	0.96616917	0.96618887	0.96619662	0.96622768
4	0.9647698	0.96529428	0.96539902	0.9658082	0.96622768
5	0.96534815	0.96605837	0.96605837	0.96607362	0.96622768
6	0.96580866	0.96596164	0.96596164	0.9659647	0.96622768
7	0.96550561	0.96580304	0.96584535	0.96590757	0.96622768
8	0.9657762	0.96616	0.96621551	0.96622675	0.96622768
9	0.96614081	0.96620108	0.96620905	0.9662268	0.96622768
10	0.96584155	0.96599542	0.96599542	0.9660439	0.96622768

GB000494_4D_D, MAXBAS_BETA_FC_LP

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



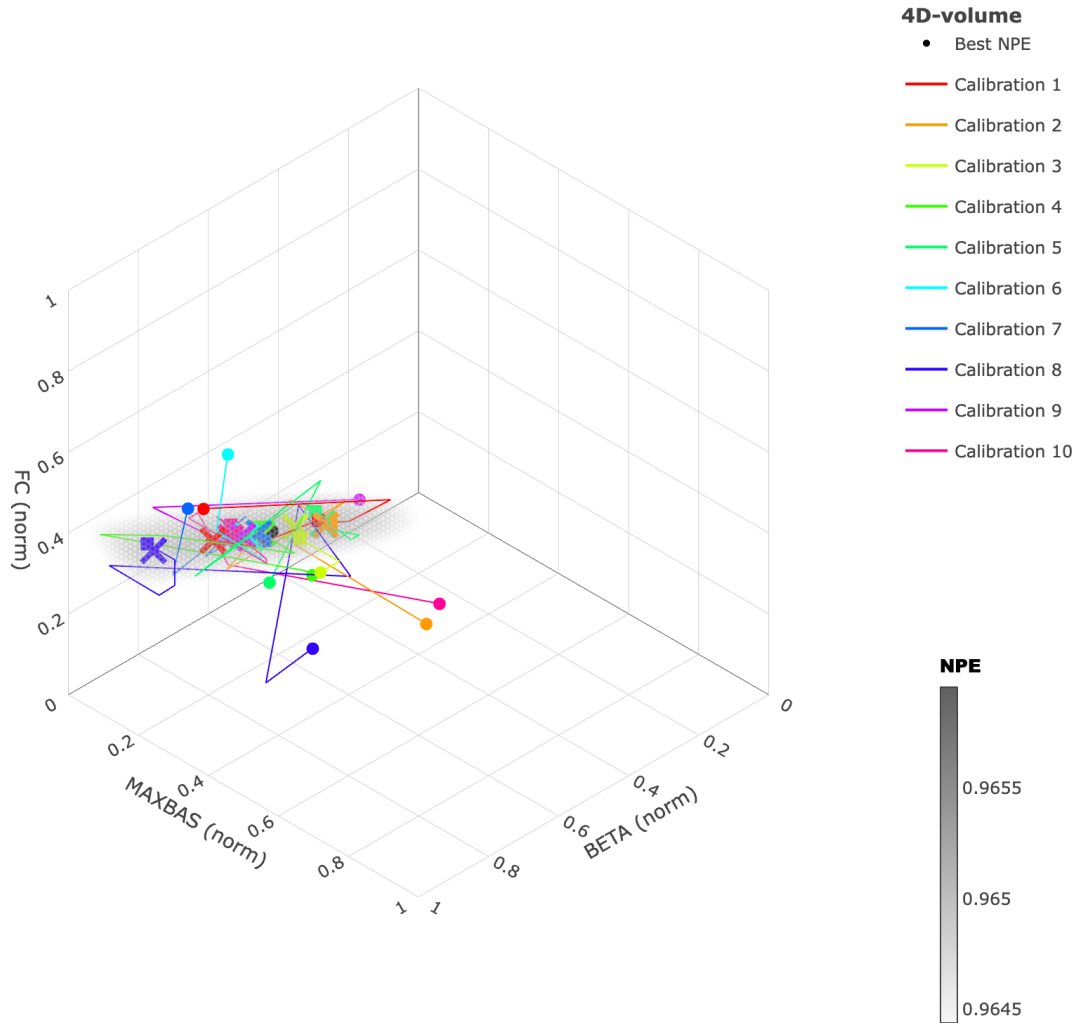
GB000494_4D_D: Persistence Diagram, top 5%



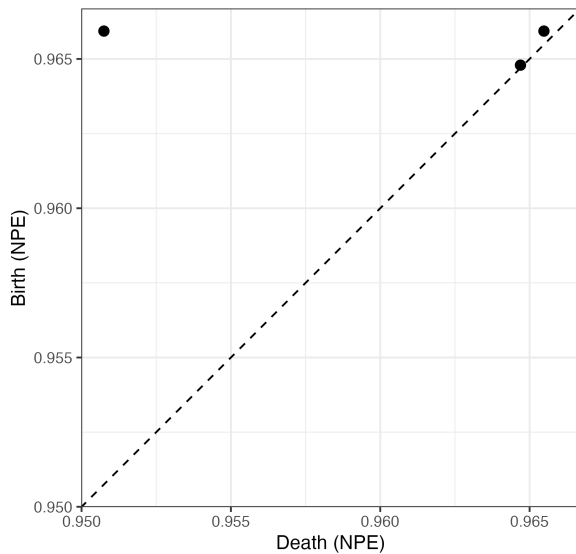
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.96512052	0.96514986	0.96515446	0.96515606	0.96514595
2	0.96497445	0.96504372	0.96504506	0.96504506	0.96514595
3	0.96421819	0.96502751	0.96502988	0.96504649	0.96514595
4	0.96496938	0.96501341	0.96502928	0.96504335	0.96514595
5	0.96490887	0.96496002	0.96496739	0.9649728	0.96514595
6	0.96438151	0.96510193	0.96513796	0.96514731	0.96514595
7	0.96479713	0.96488326	0.96489617	0.96489978	0.96514595
8	0.96493434	0.96504695	0.96507869	0.96509153	0.96514595
9	0.96500774	0.96510029	0.96510029	0.96510714	0.96514595
10	0.96511183	0.96515005	0.96515273	0.96515464	0.96514595

GB000494_4D_E, MAXBAS_BETA_FC_LP

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



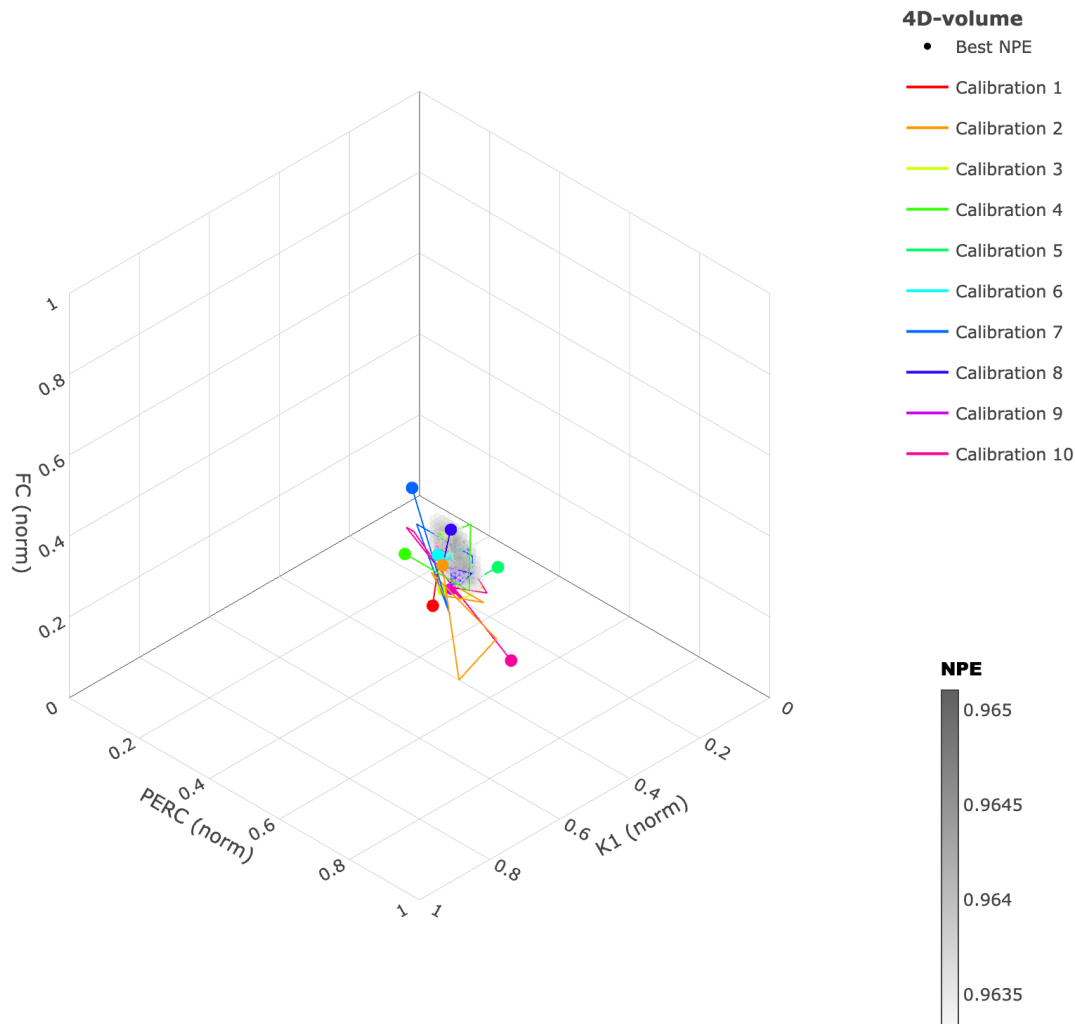
GB000494_4D_E: Persistence Diagram, top 5%



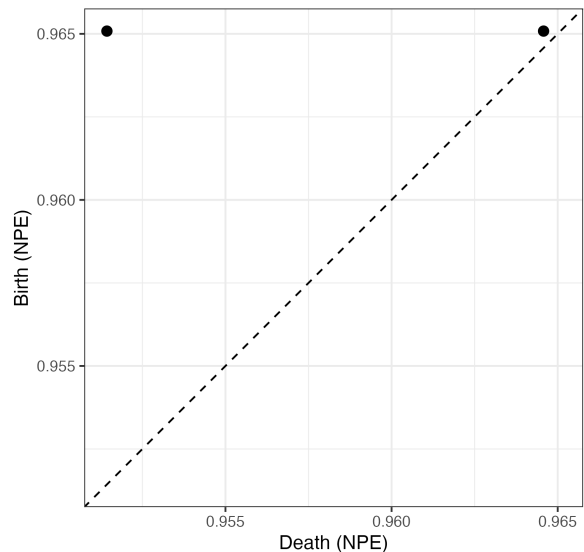
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.96560215	0.96583729	0.96586657	0.96587008	0.96595613
2	0.96577996	0.96581775	0.96586626	0.96587012	0.96595613
3	0.96576258	0.96594374	0.96594392	0.96594711	0.96595613
4	0.96587768	0.96594281	0.96595377	0.96595532	0.96595613
5	0.96543547	0.96583367	0.96583367	0.96586452	0.96595613
6	0.96569993	0.96592719	0.96592719	0.96593212	0.96595613
7	0.9658219	0.96595063	0.96595238	0.96595504	0.96595613
8	0.96560589	0.96565728	0.96566296	0.96566622	0.96595613
9	0.9659171	0.96593008	0.96593401	0.96593401	0.96595613
10	0.96575685	0.96590819	0.96591198	0.96591198	0.96595613

GB000494_4D_J, PERC_K1_FC_CFMAX

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs



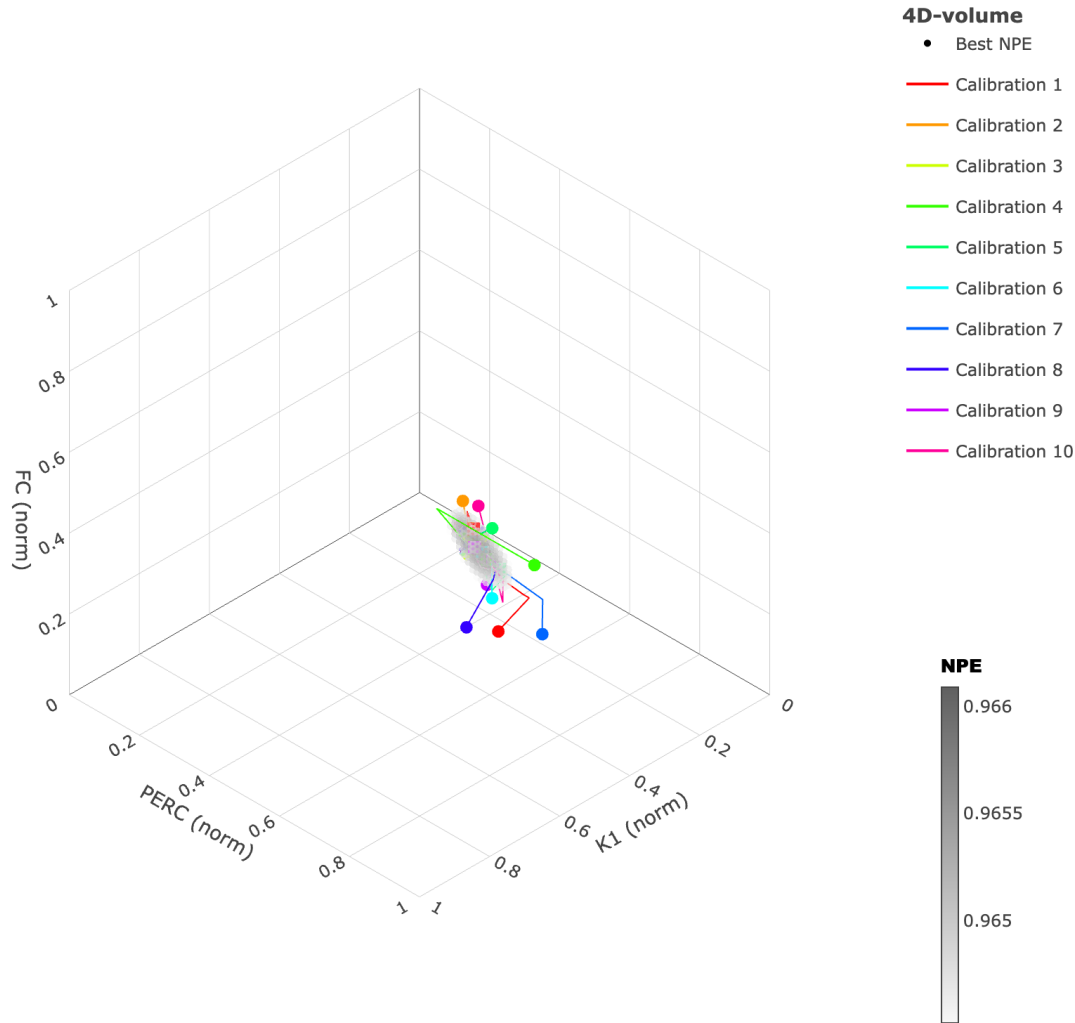
GB000494_4D_J: Persistence Diagram, top 5%



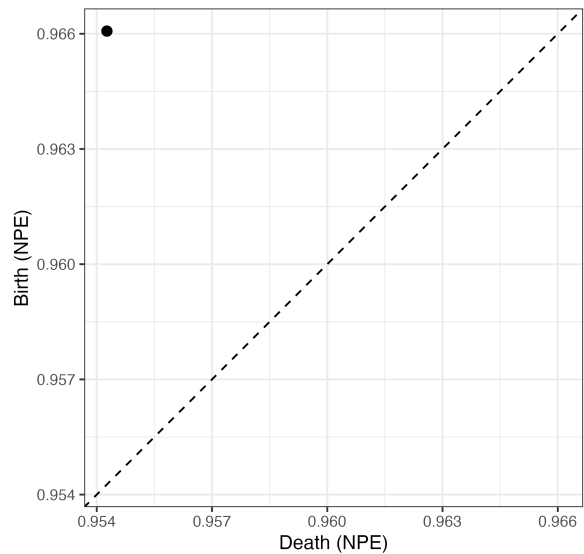
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.9649264	0.96510283	0.96512195	0.96514435	0.9651029
2	0.96438357	0.96497863	0.96509191	0.96511634	0.9651029
3	0.96435647	0.96510729	0.96512038	0.96514262	0.9651029
4	0.96498505	0.96511716	0.96512467	0.96512746	0.9651029
5	0.96500784	0.96510003	0.96510749	0.96512845	0.9651029
6	0.96454297	0.96497533	0.96511643	0.96514168	0.9651029
7	0.96446262	0.96513159	0.96514062	0.96514575	0.9651029
8	0.96405092	0.96466526	0.96489746	0.96511479	0.9651029
9	0.96487843	0.96512614	0.96513767	0.96514119	0.9651029
10	0.96457629	0.96489827	0.96501147	0.96513498	0.9651029

GB000494_4D_K, PERC_K1_FC_CFMAX

GA Paths & Milestones over 3D Projection of top 0.1% NPE zones
circle = 50 runs, square = 1'000 runs, cross = 10'000 runs

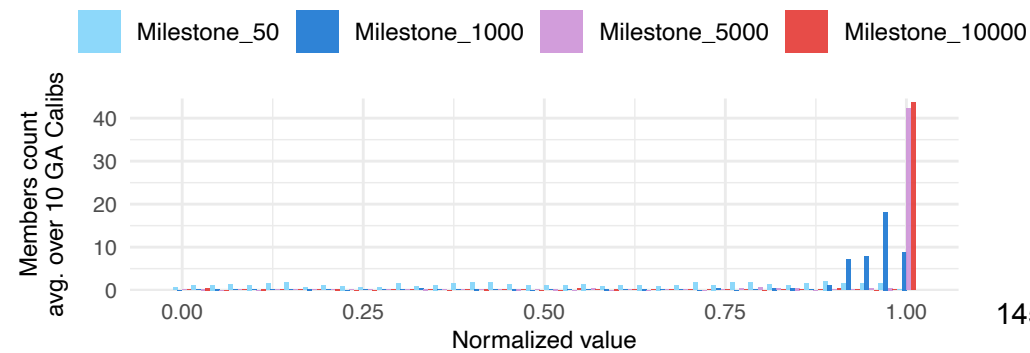
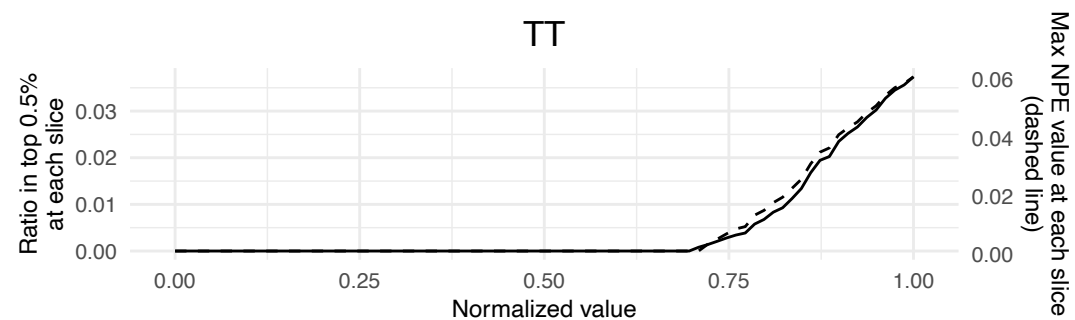
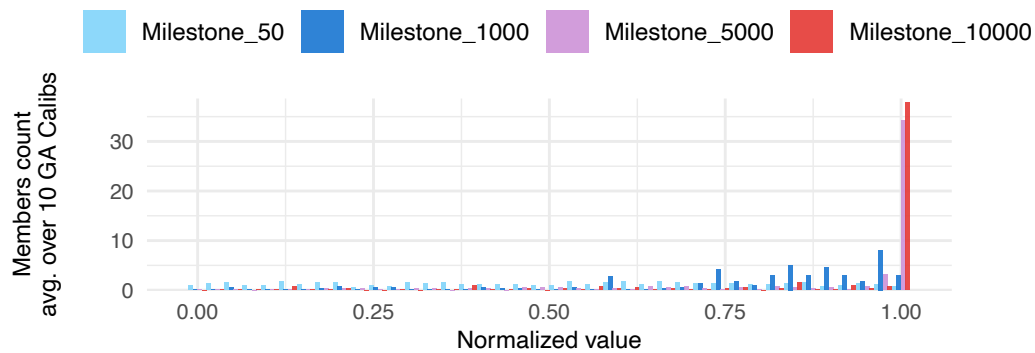
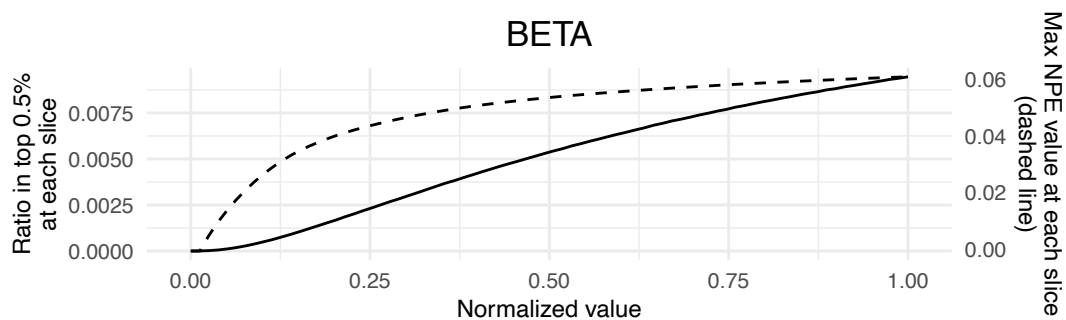
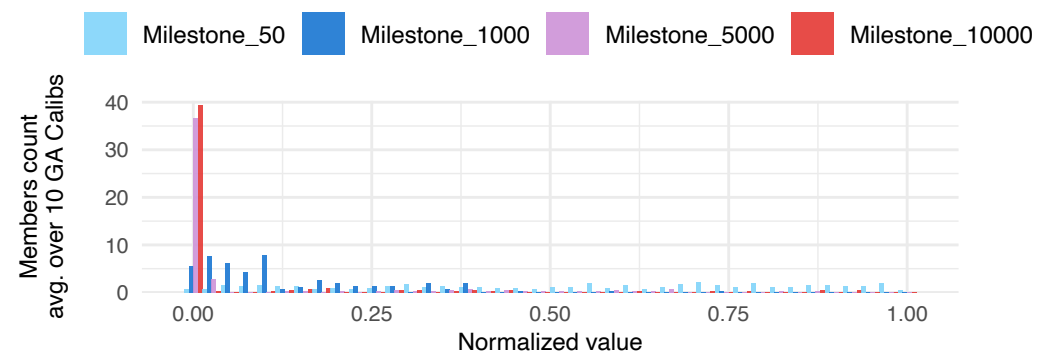
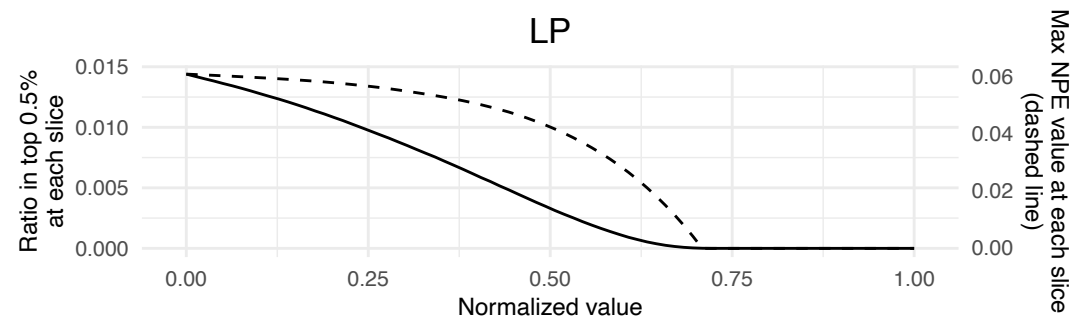
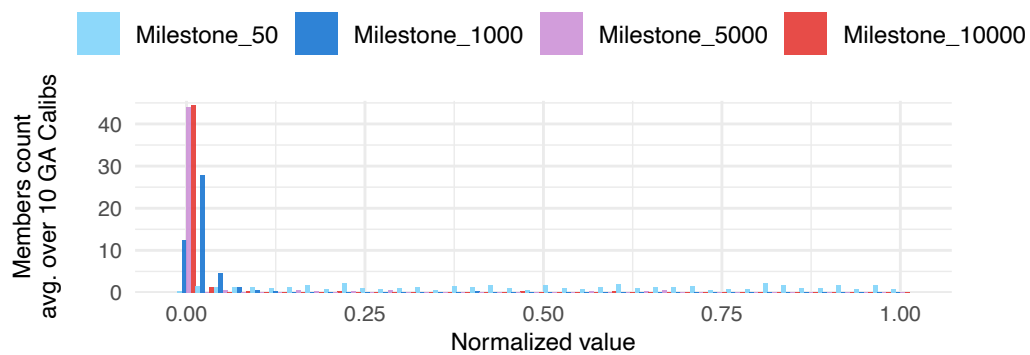
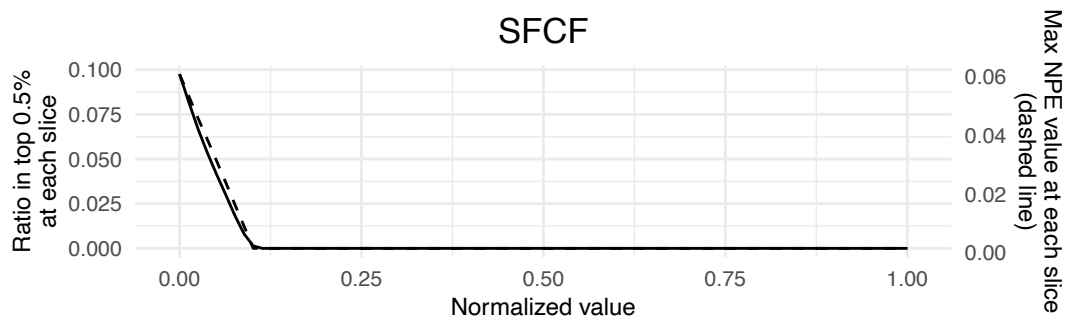


GB000494_4D_K: Persistence Diagram, top 5%



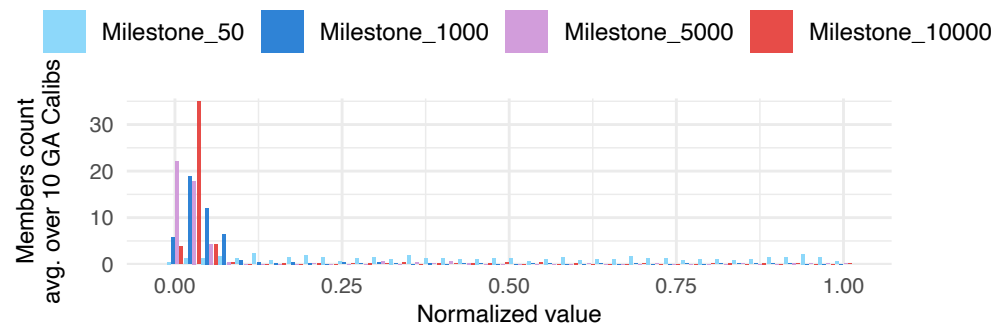
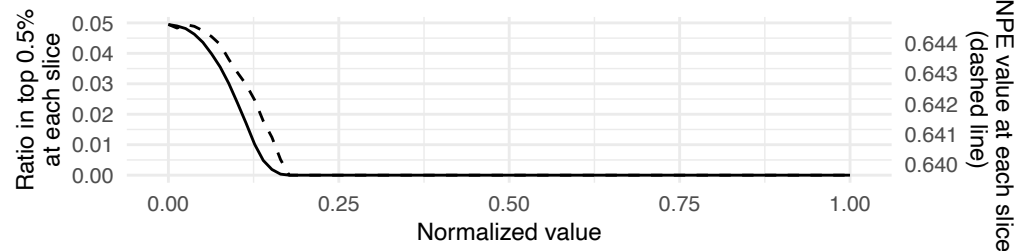
CALIB	NPE_1000	NPE_3000	NPE_5000	NPE_10000	NPE_best
1	0.96532124	0.96609001	0.96609359	0.96609653	0.96608702
2	0.96510081	0.96571246	0.96604173	0.96608039	0.96608702
3	0.9659831	0.9660162	0.96603473	0.96606039	0.96608702
4	0.96579031	0.96608612	0.96609575	0.96609575	0.96608702
5	0.96512996	0.96593246	0.96608377	0.96609675	0.96608702
6	0.96595673	0.96596771	0.96606639	0.96609267	0.96608702
7	0.96585185	0.96605307	0.96608652	0.96609832	0.96608702
8	0.96590158	0.9660503	0.96605278	0.96606287	0.96608702
9	0.96573366	0.96606933	0.96609206	0.96609613	0.96608702
10	0.96534992	0.96604168	0.96608511	0.96609659	0.96608702

2155_4D_A: 4D Coverage & NPE Profiles

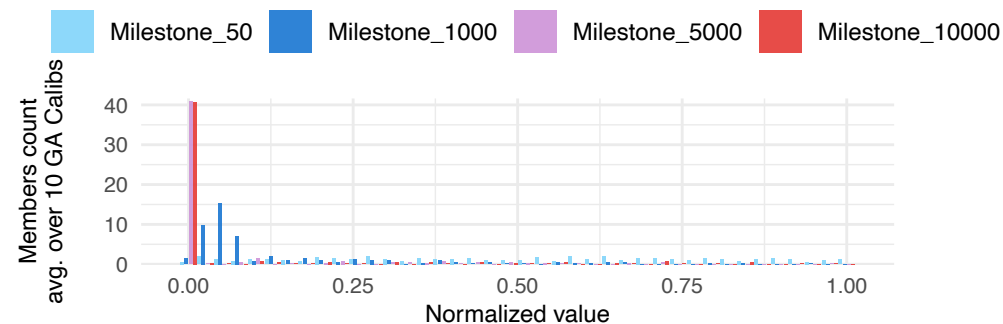
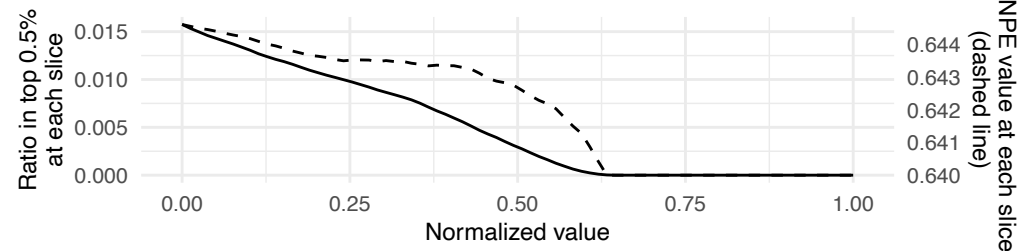


2155_4D_B: 4D Coverage & NPE Profiles

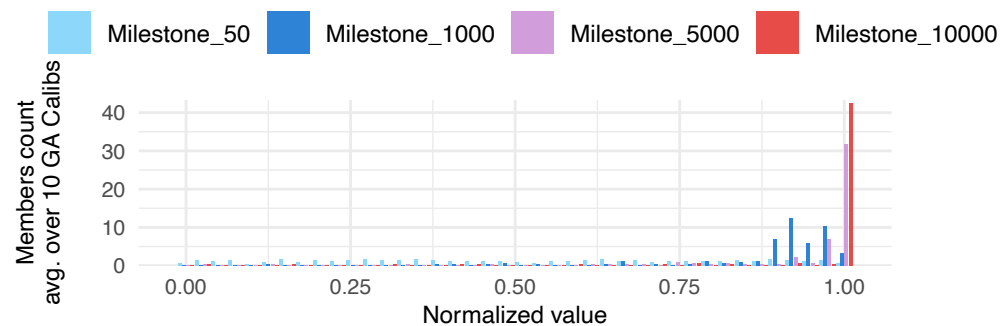
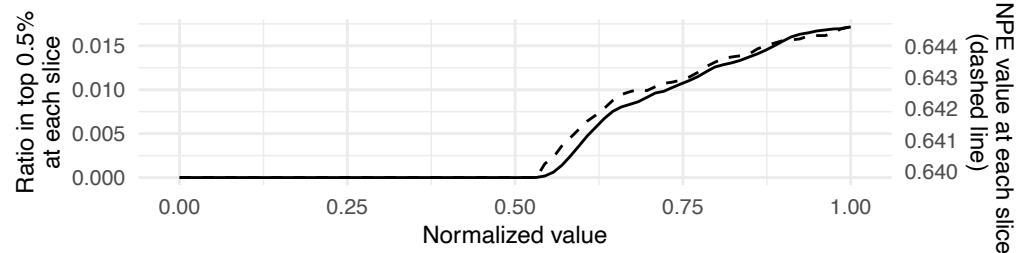
SFCF



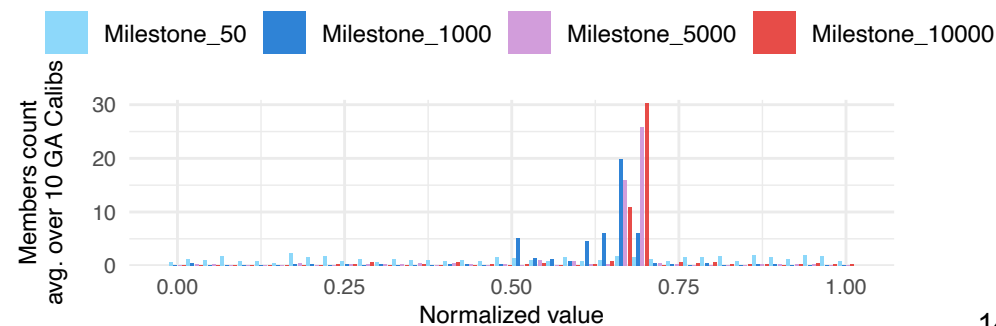
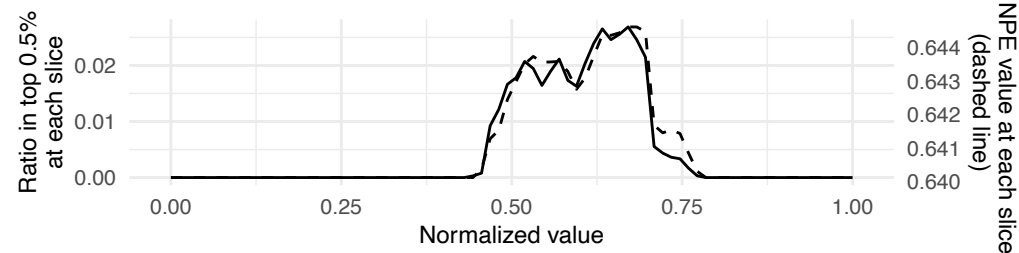
LP



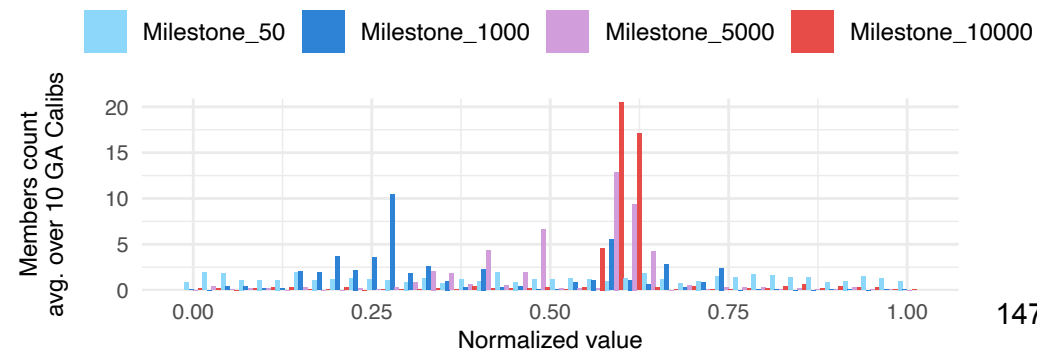
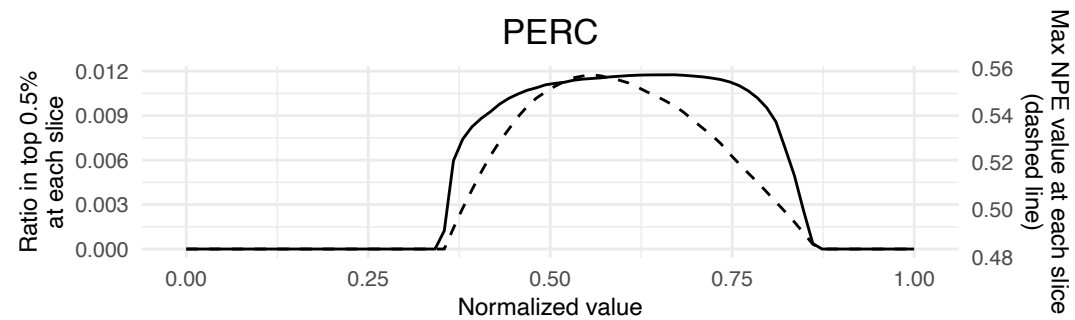
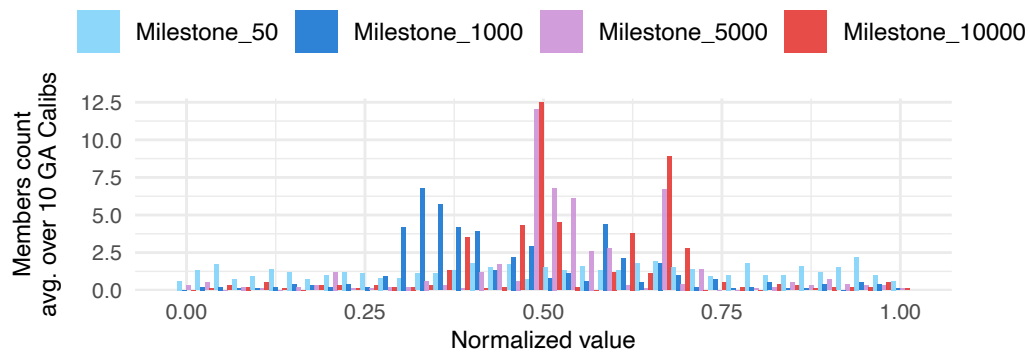
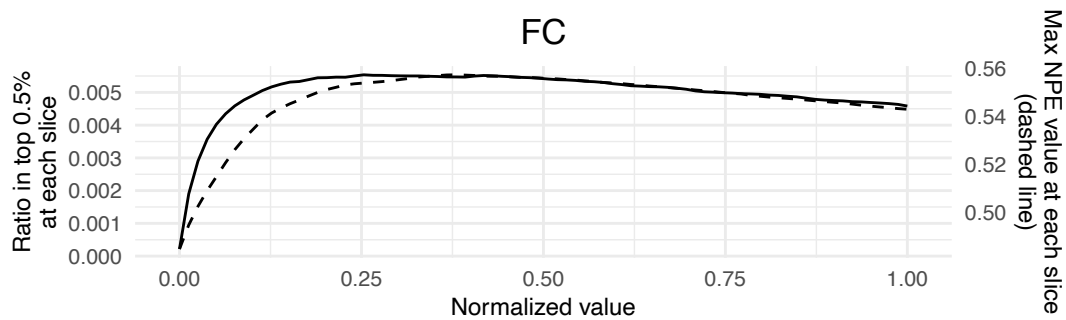
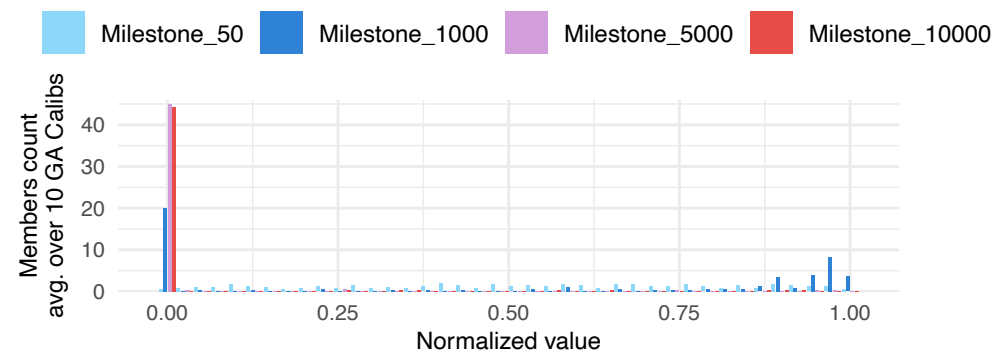
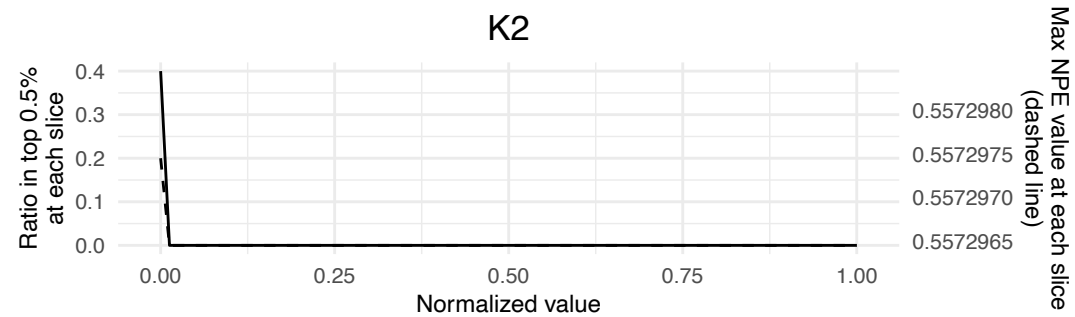
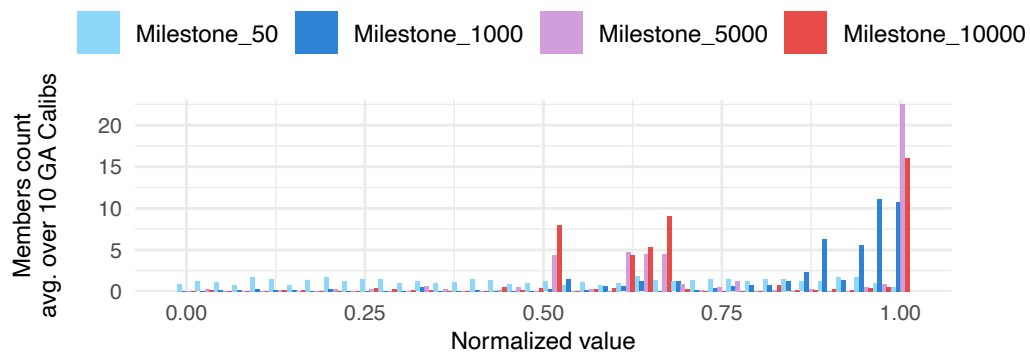
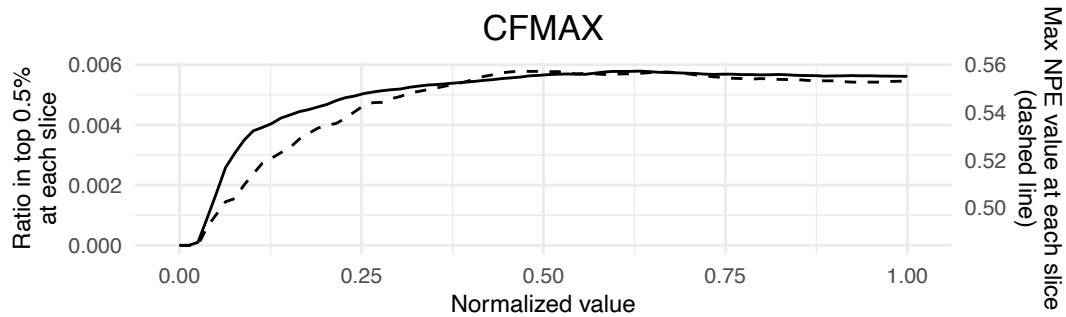
BETA



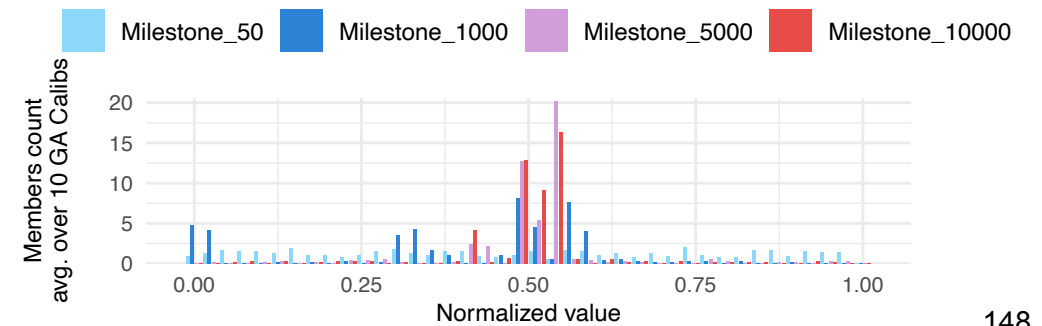
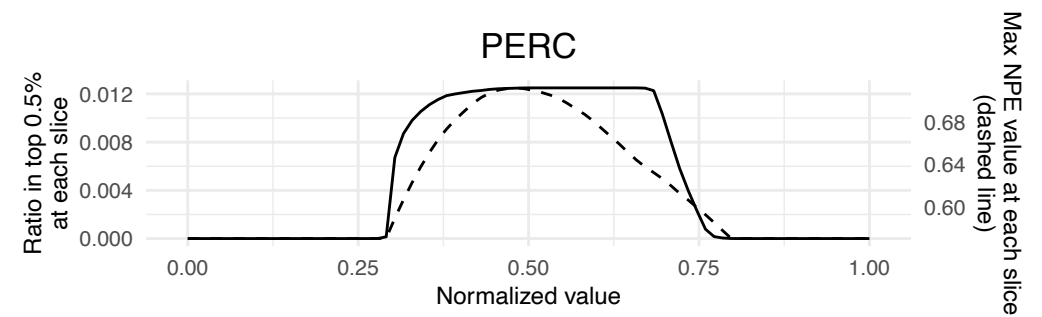
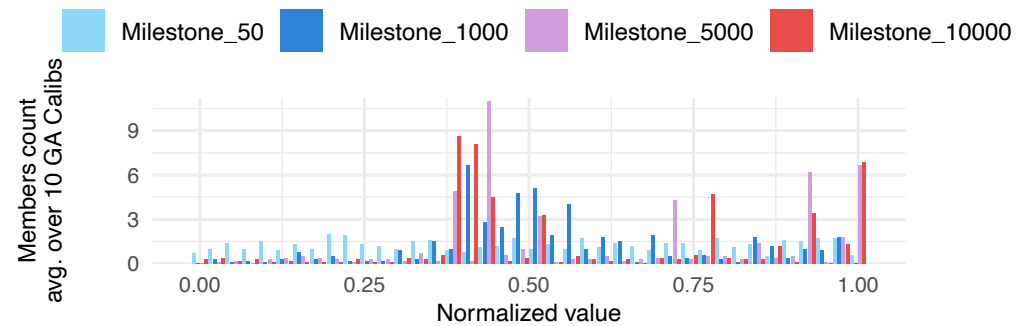
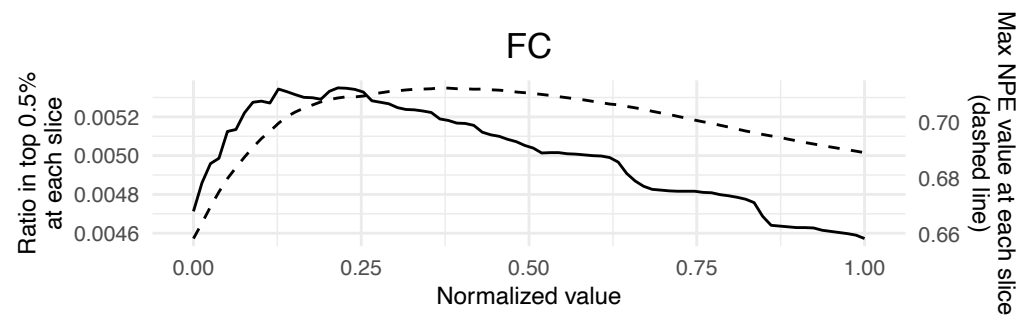
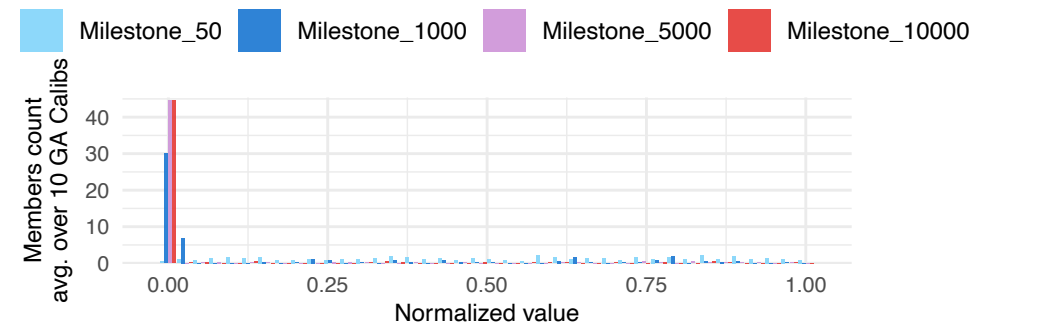
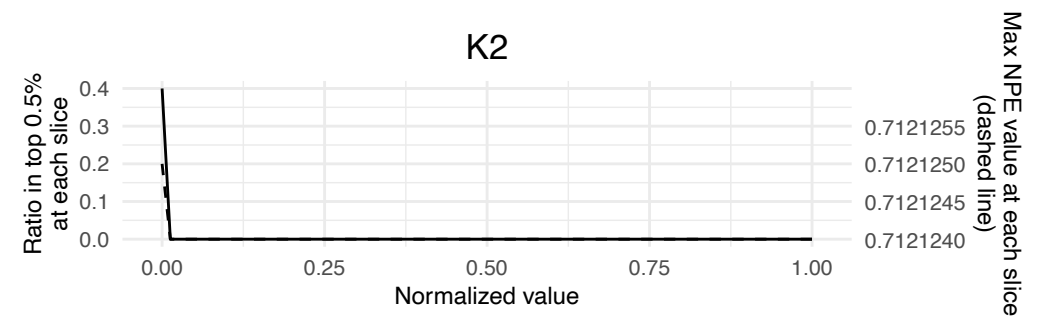
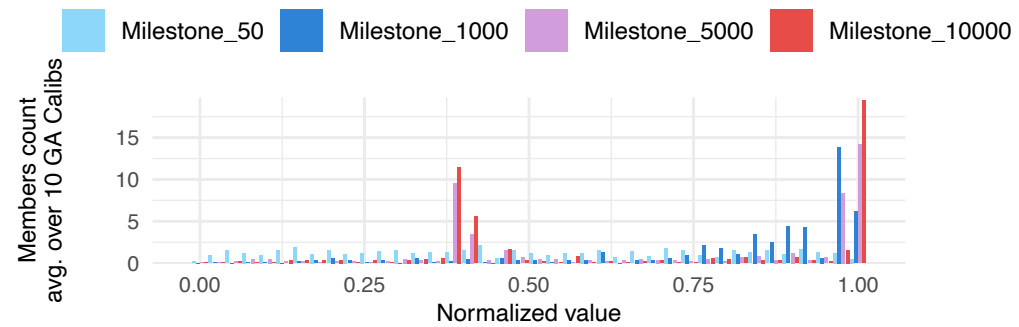
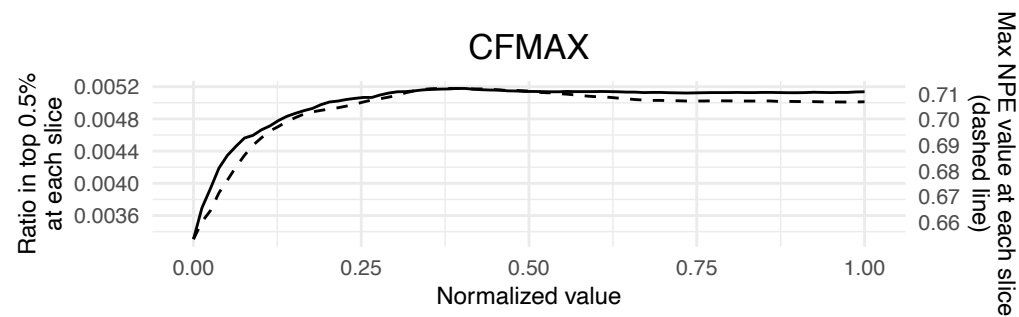
TT



2155_4D_D: 4D Coverage & NPE Profiles

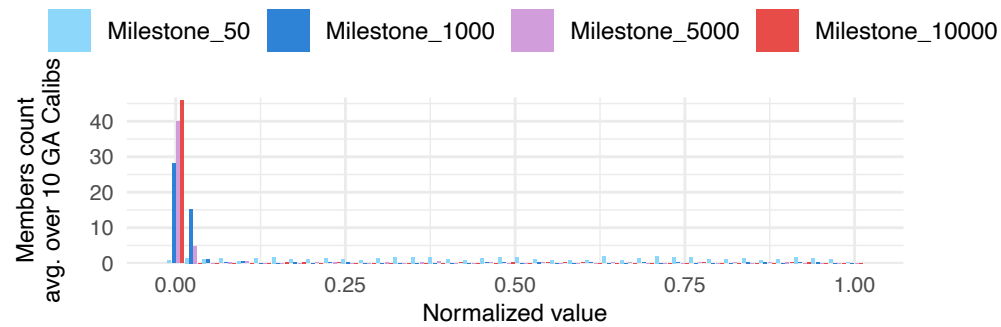
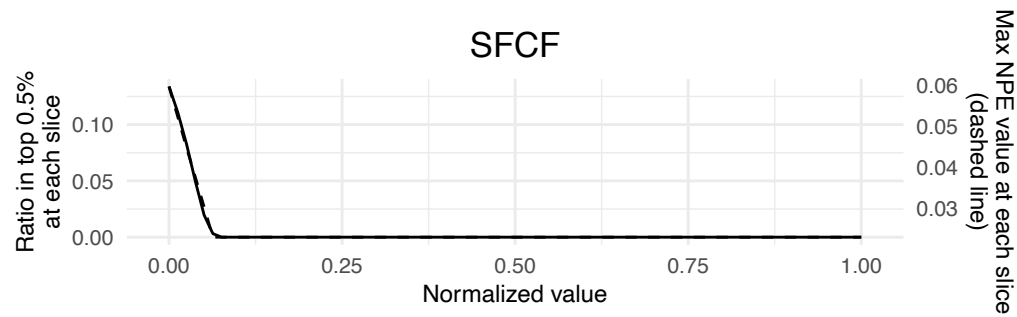


2155_4D_E: 4D Coverage & NPE Profiles

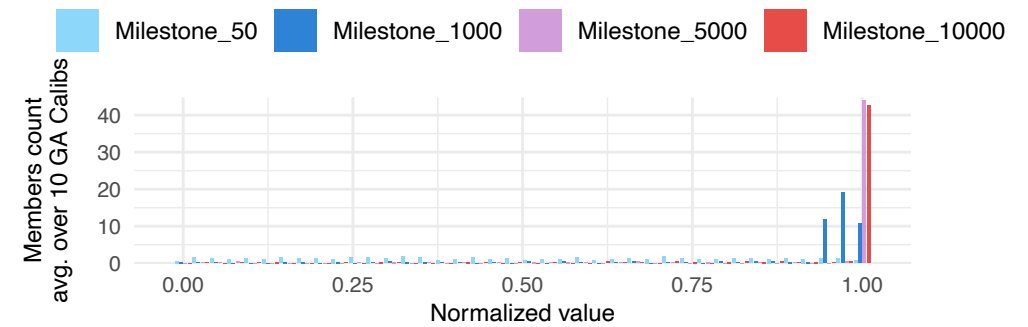
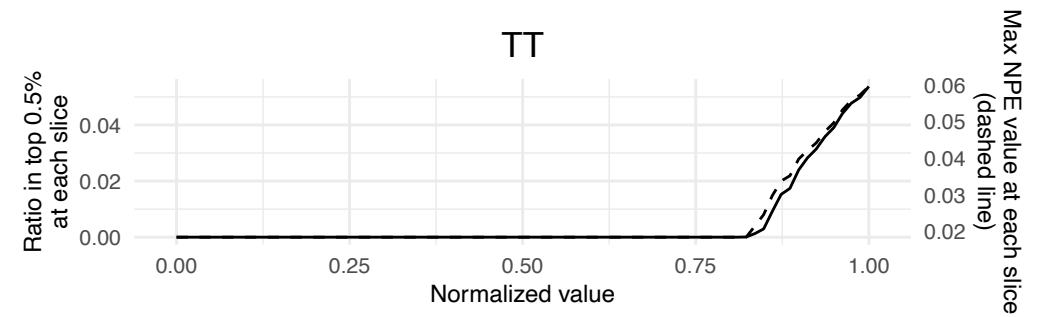


2155_4D_J: 4D Coverage & NPE Profiles

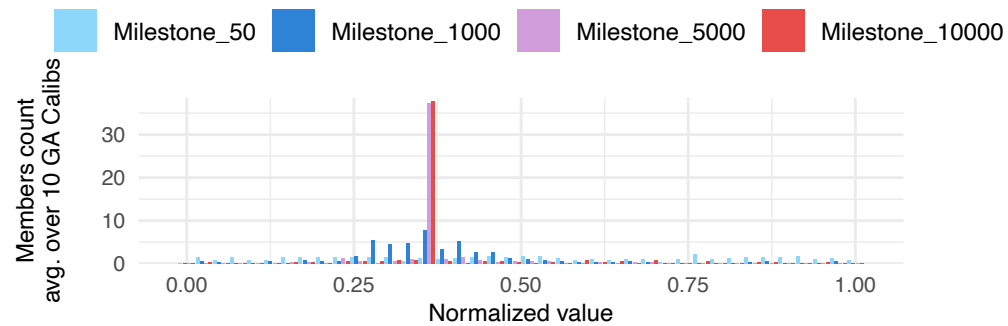
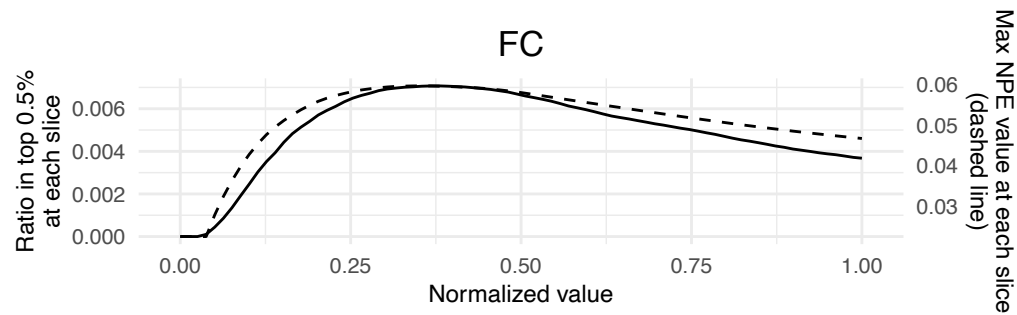
SFCF



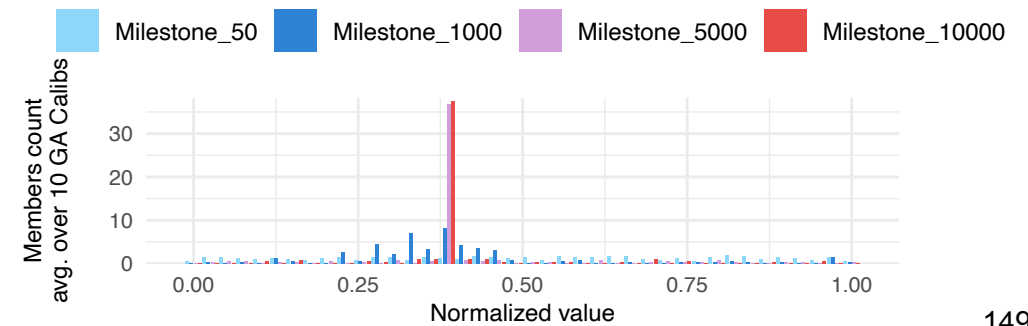
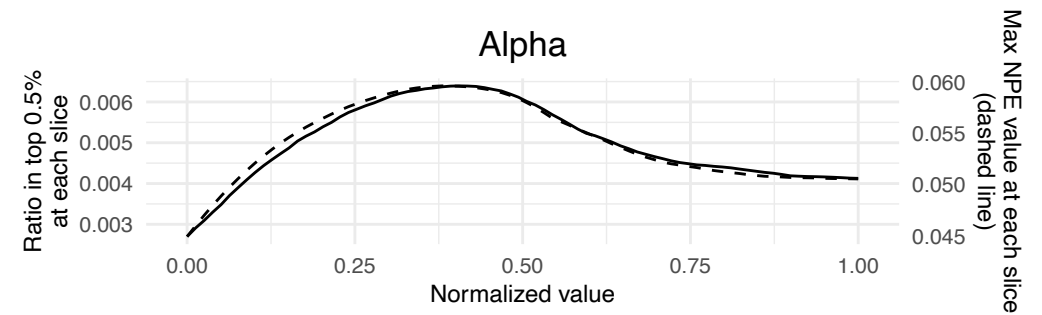
TT



FC

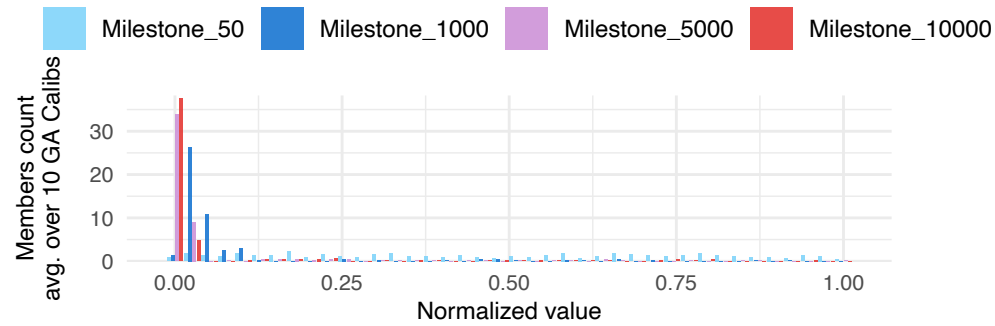
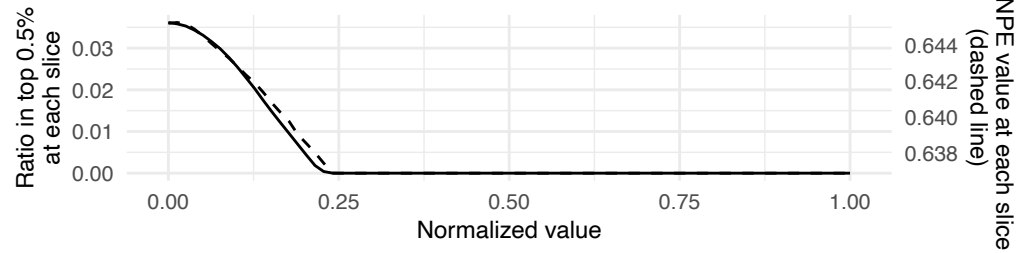


Alpha

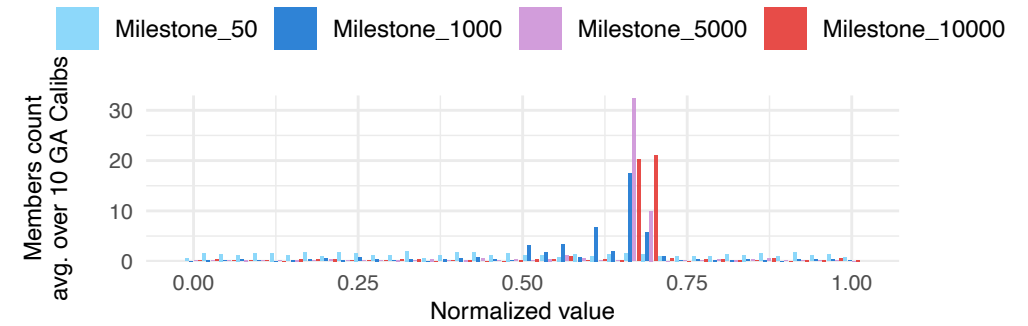
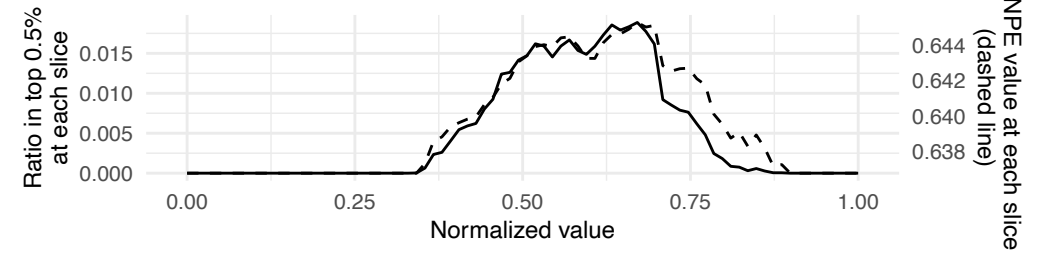


2155_4D_K: 4D Coverage & NPE Profiles

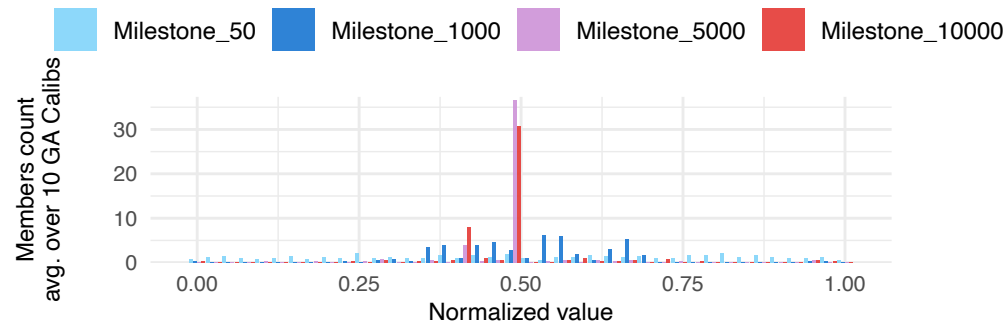
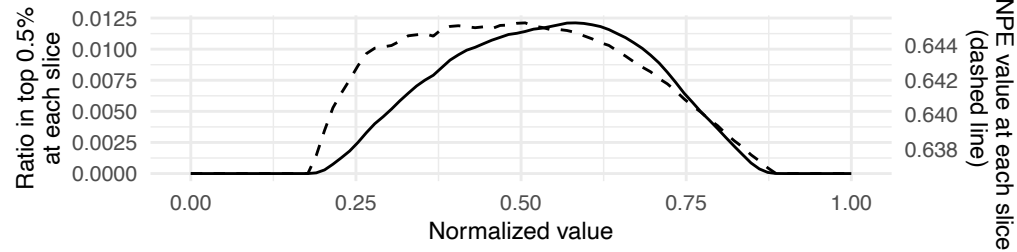
SFCF



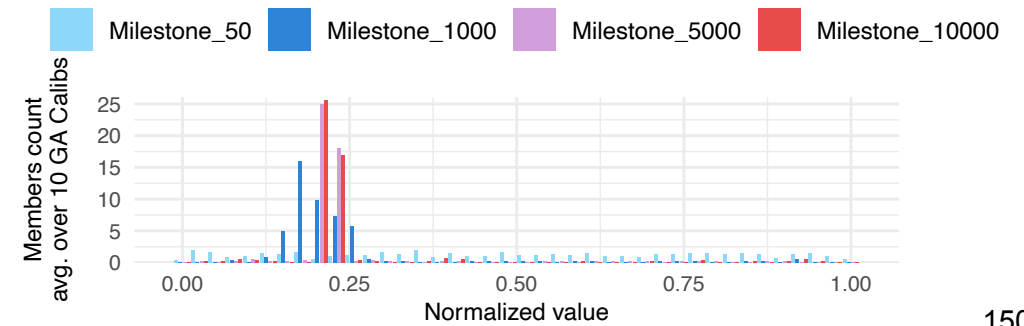
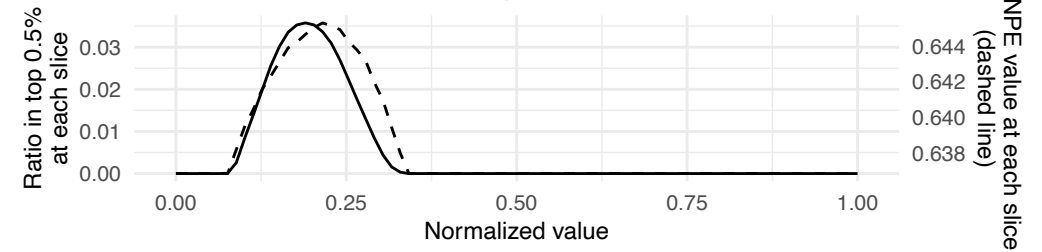
TT



FC

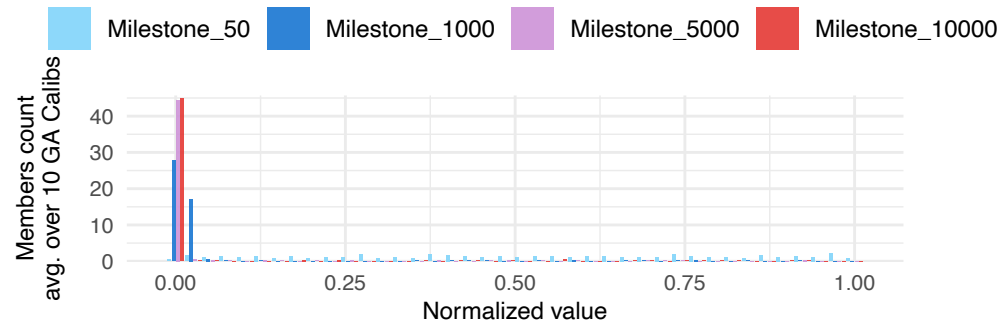
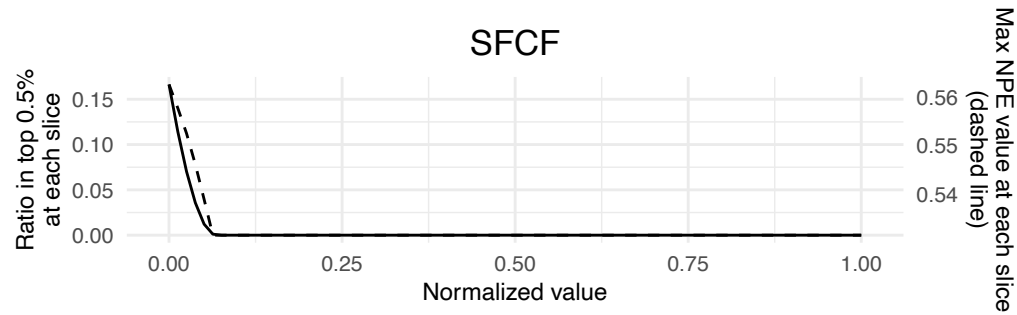


Alpha

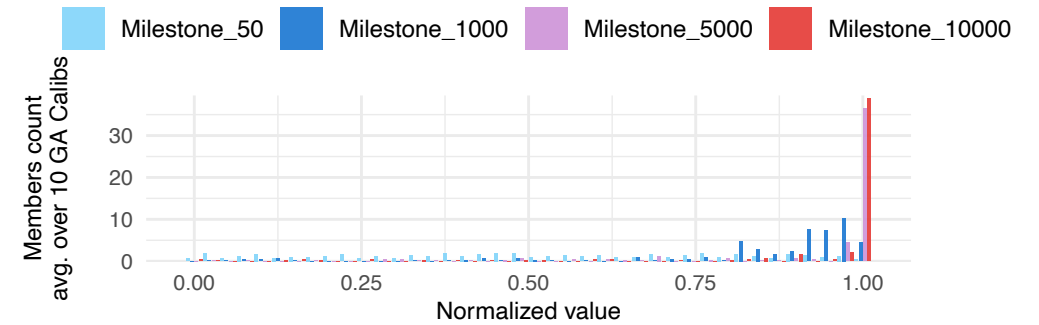
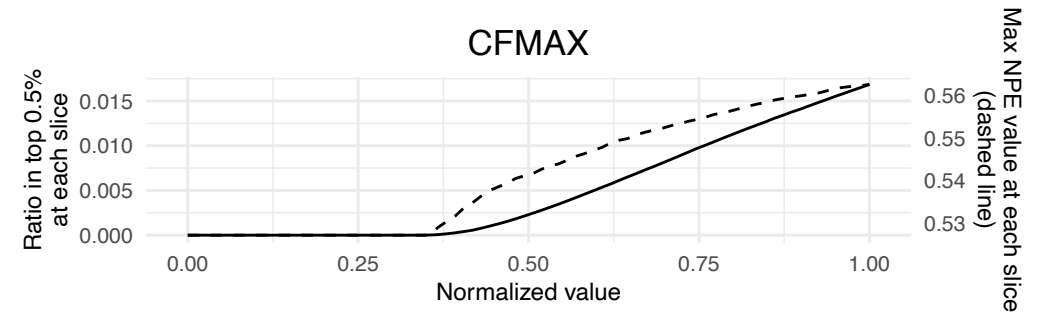


2403_4D_A: 4D Coverage & NPE Profiles

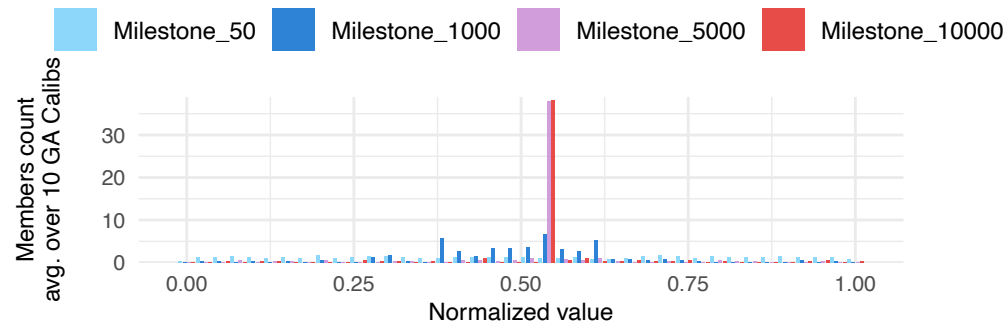
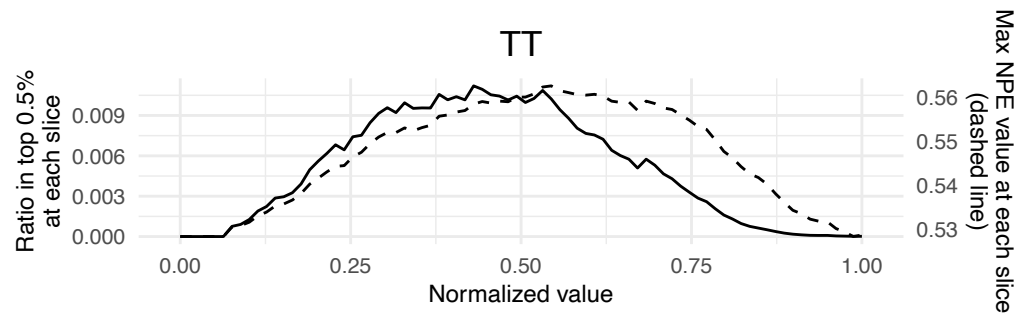
SFCF



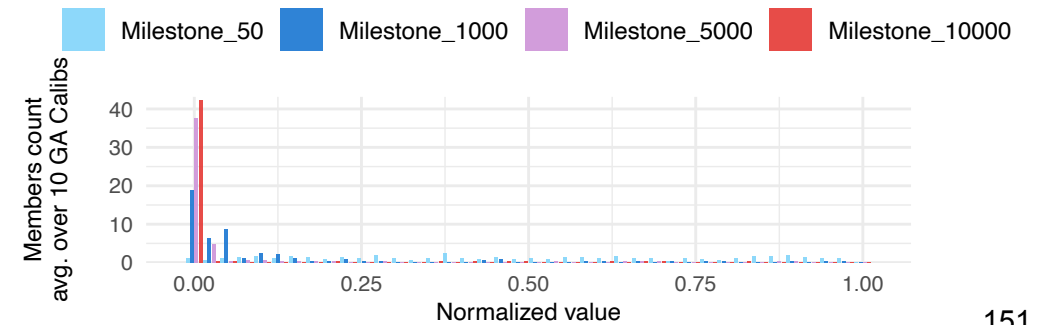
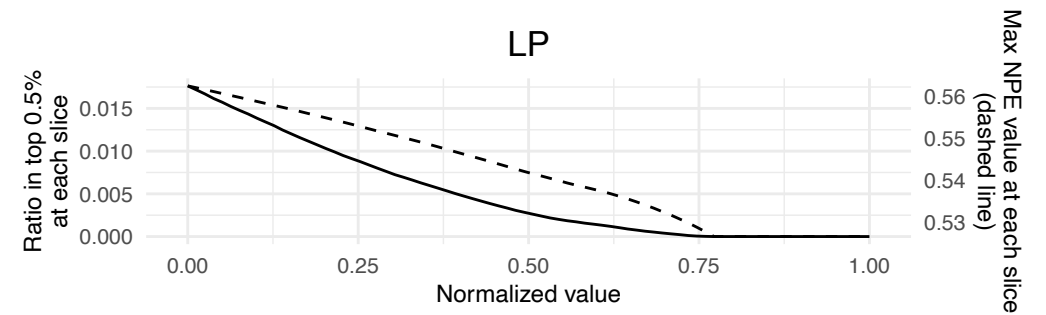
CFMAX



TT

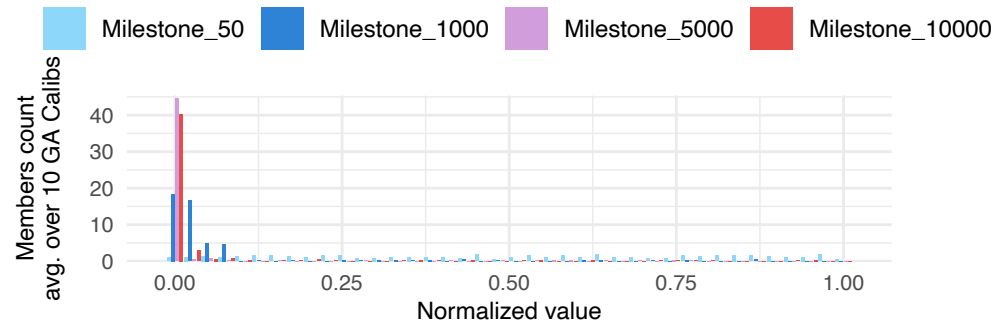
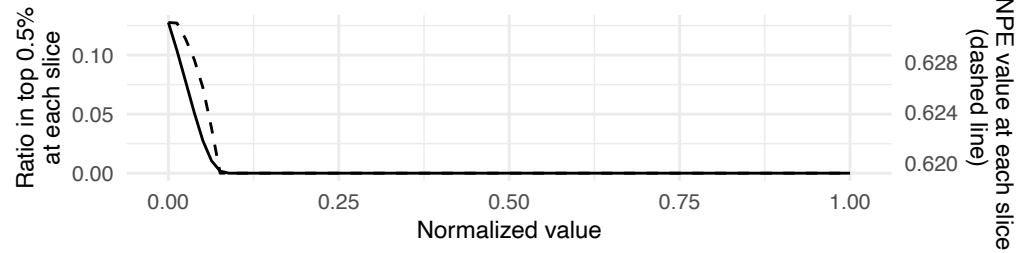


LP

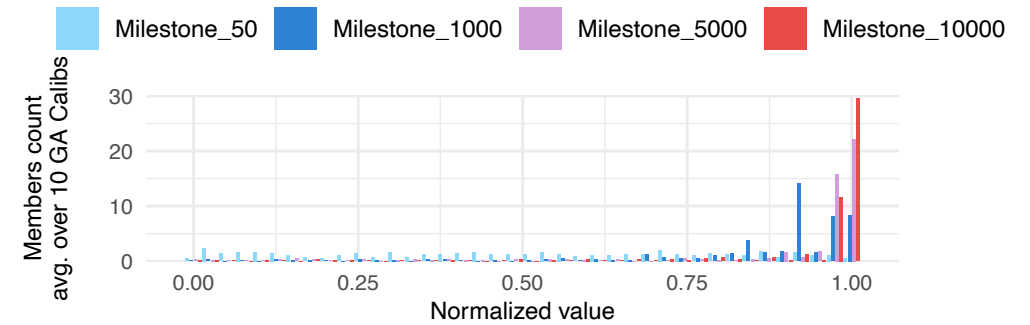
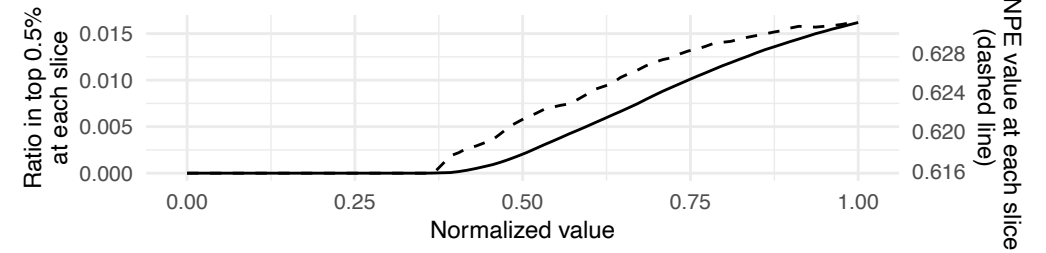


2403_4D_B: 4D Coverage & NPE Profiles

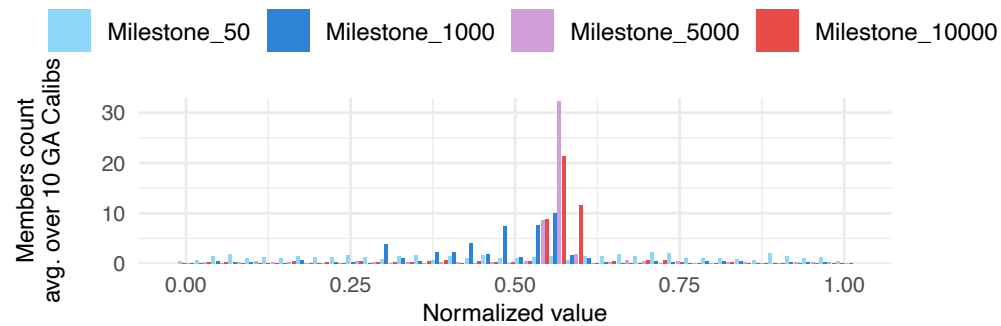
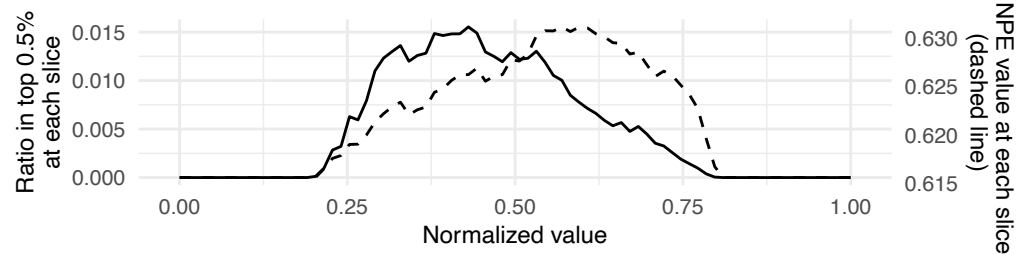
SFCF



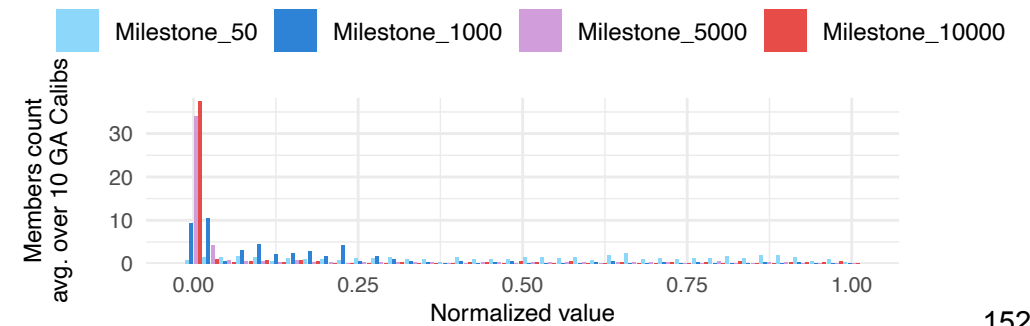
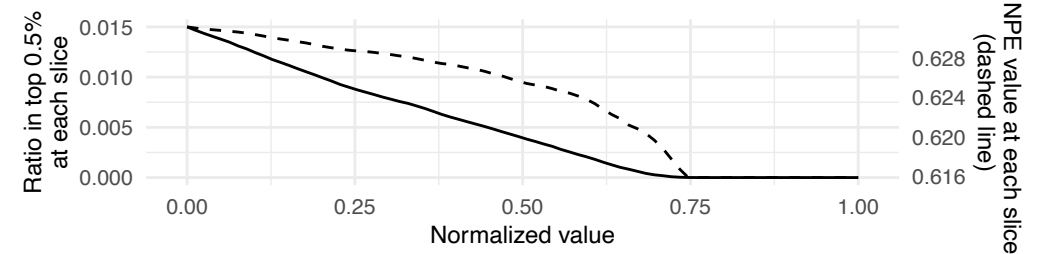
CFMAX



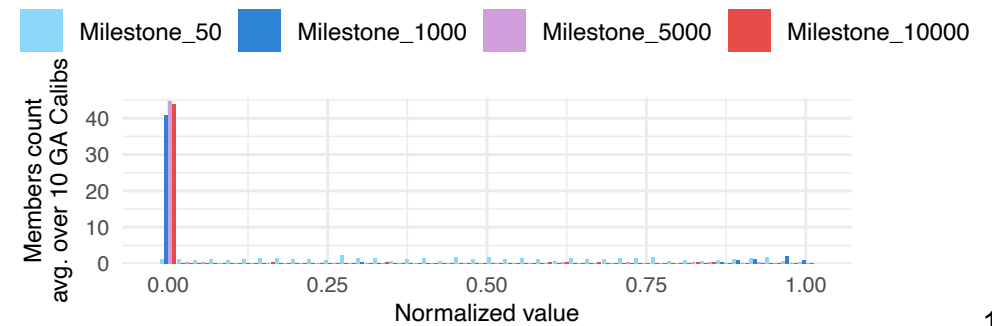
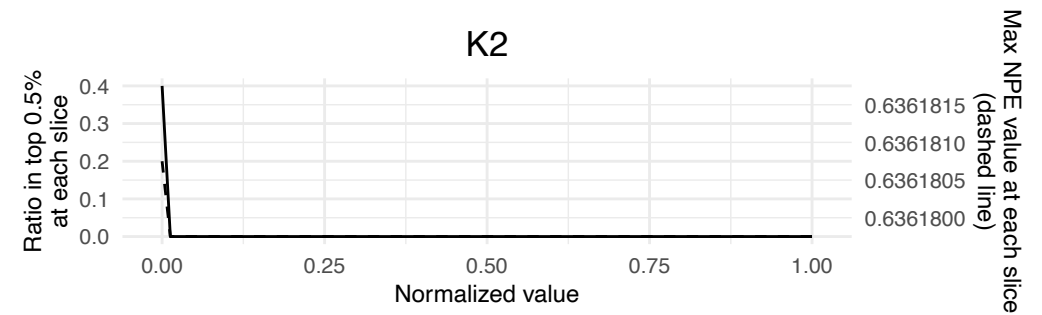
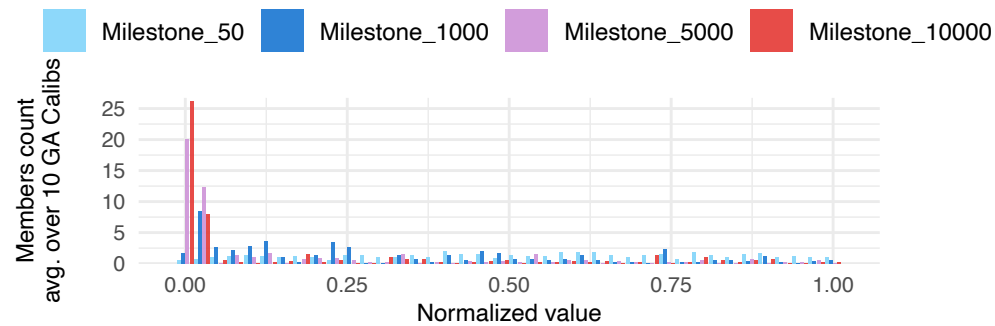
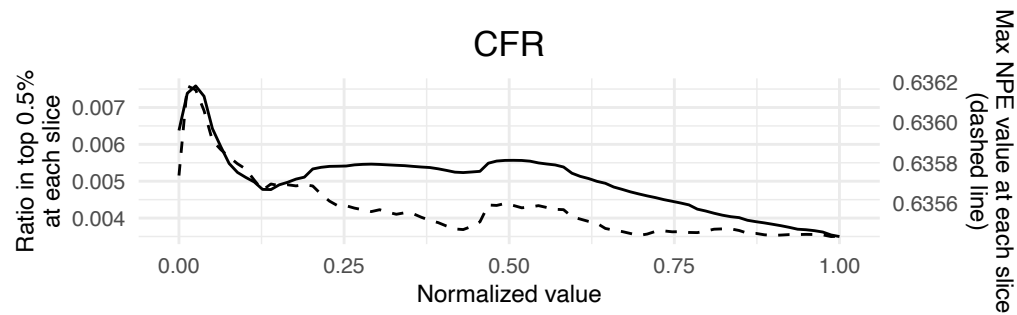
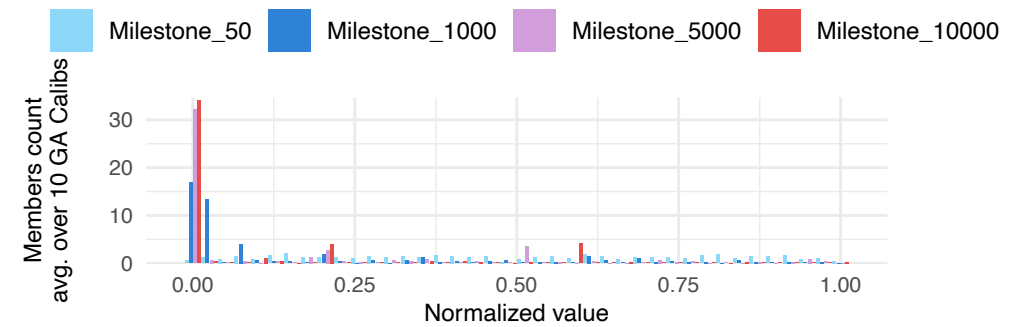
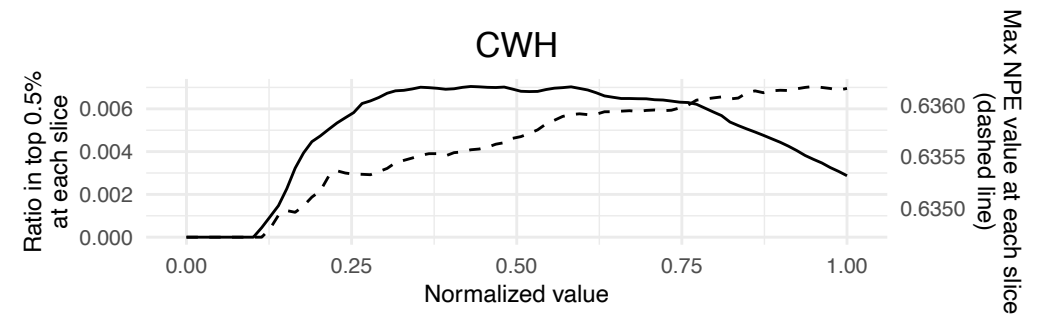
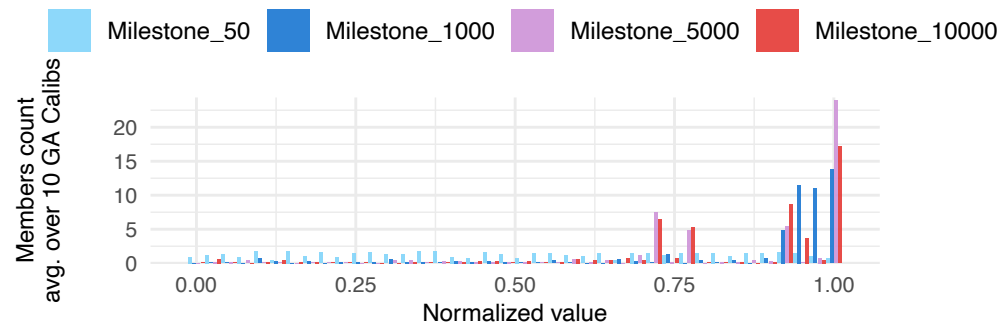
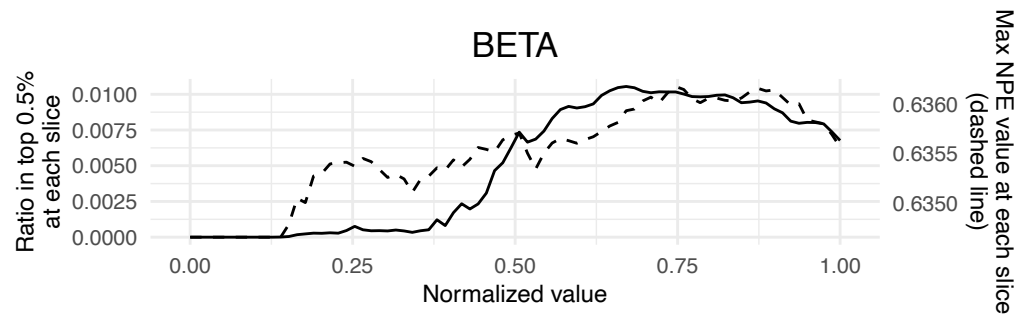
TT



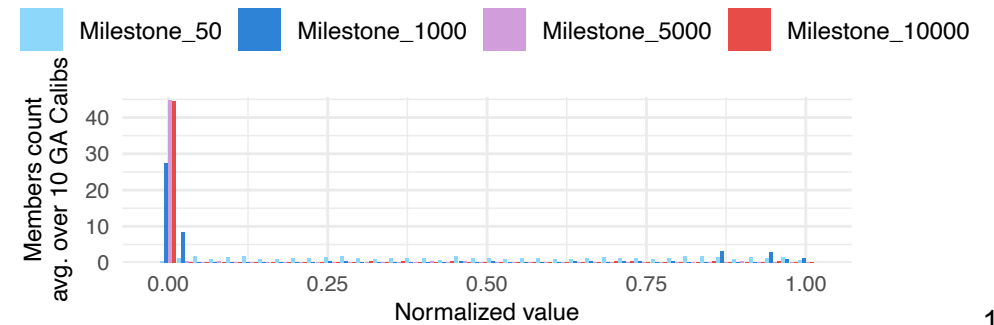
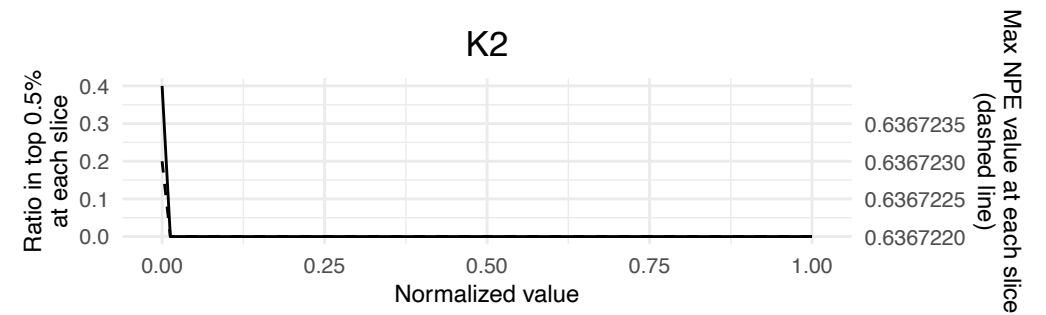
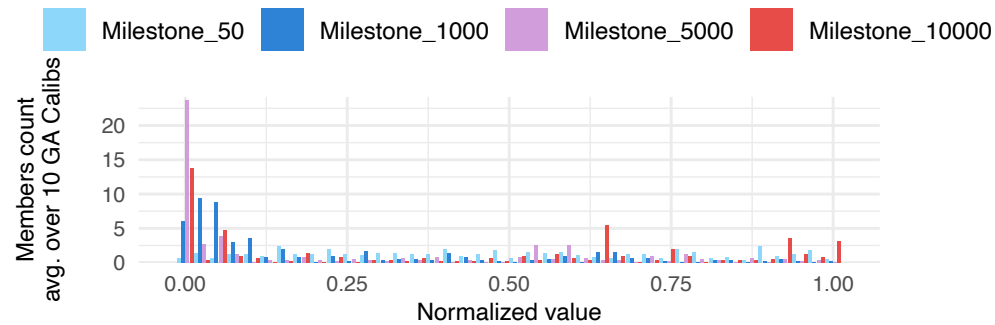
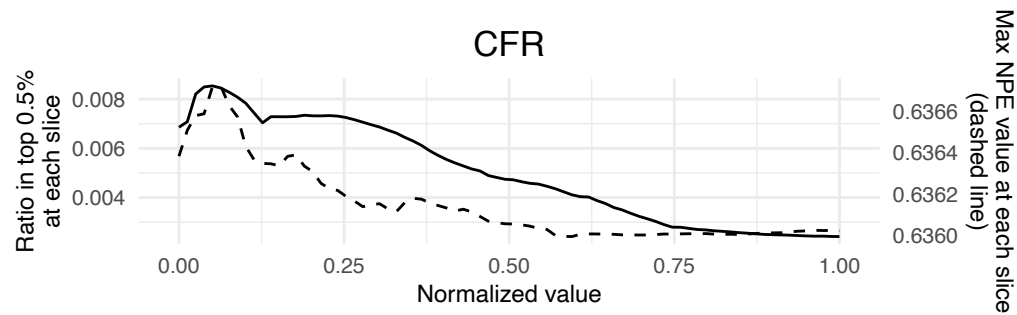
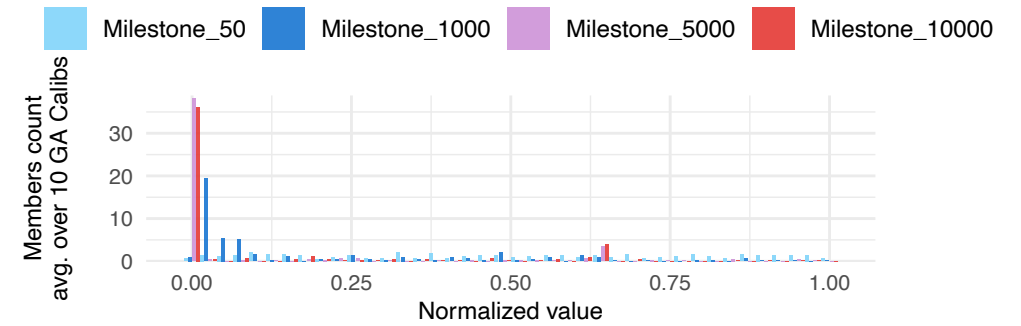
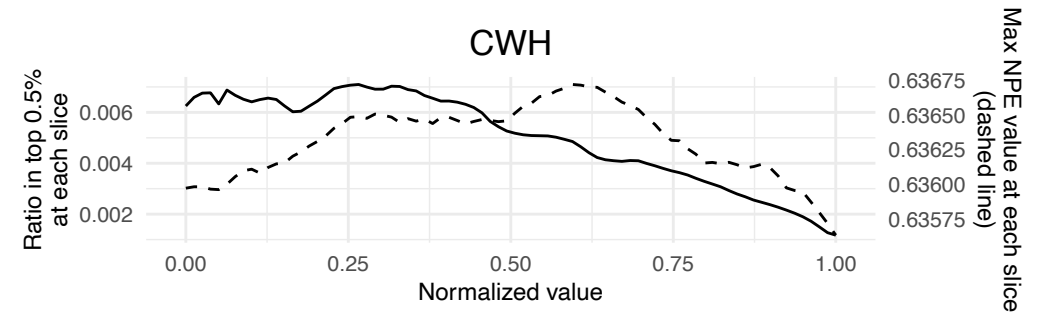
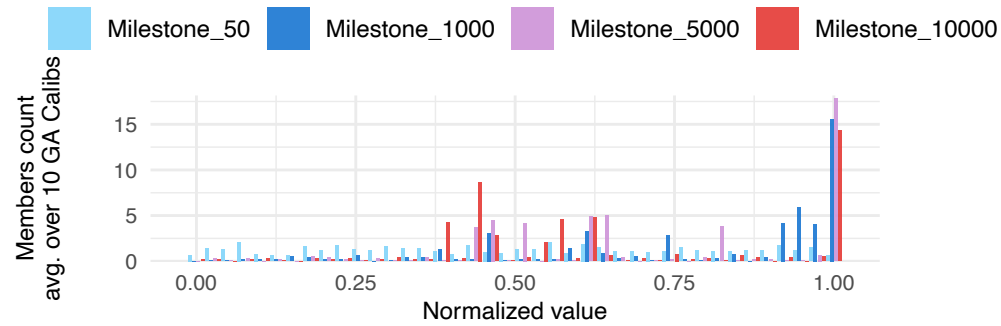
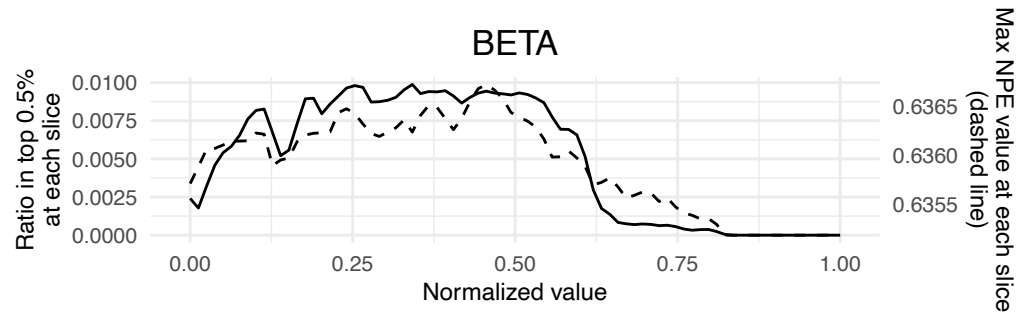
LP



2403_4D_D: 4D Coverage & NPE Profiles

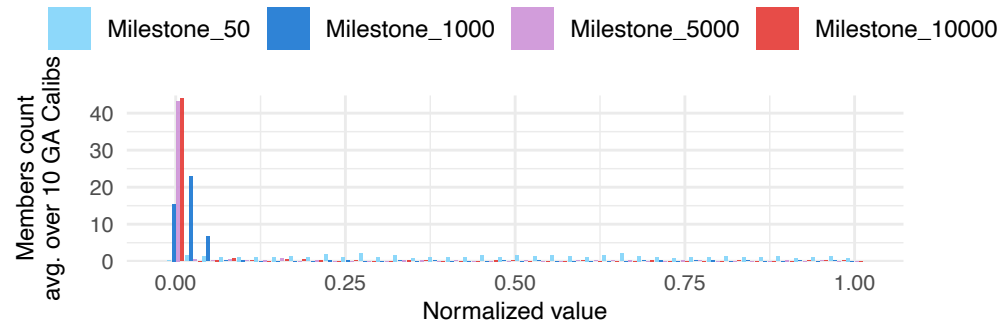
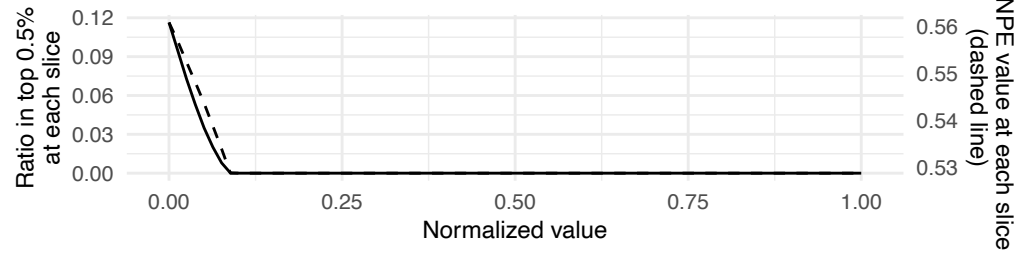


2403_4D_E: 4D Coverage & NPE Profiles

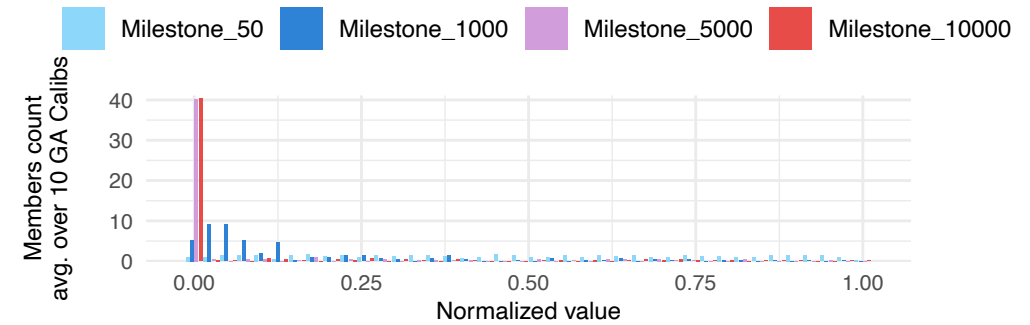
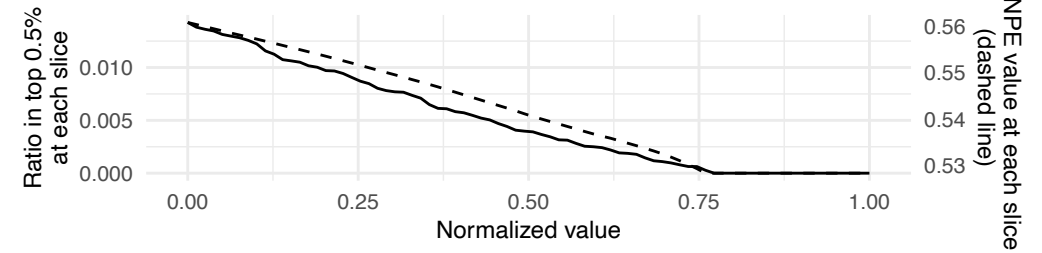


2403_4D_J: 4D Coverage & NPE Profiles

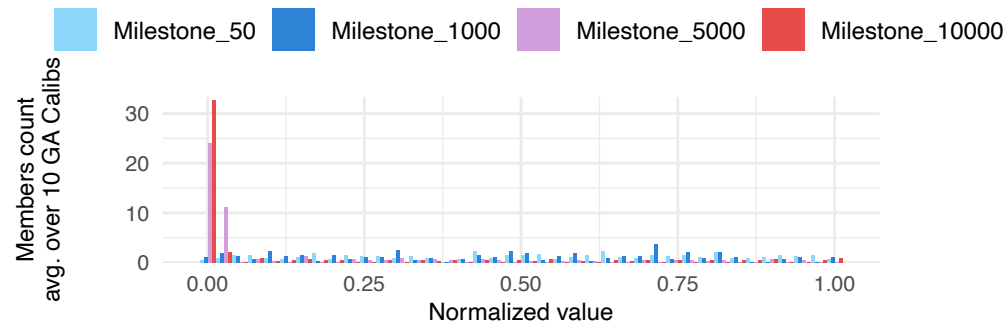
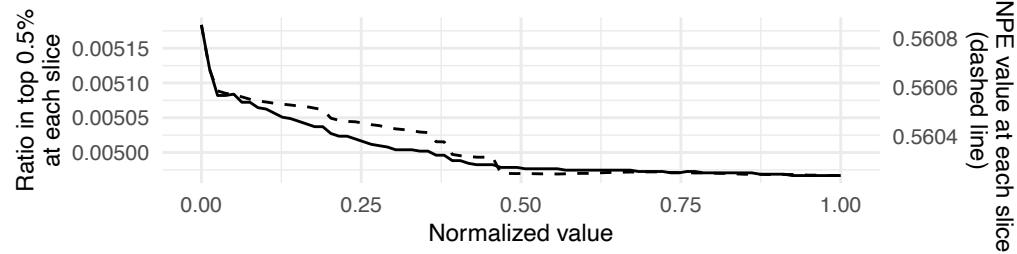
SFCF



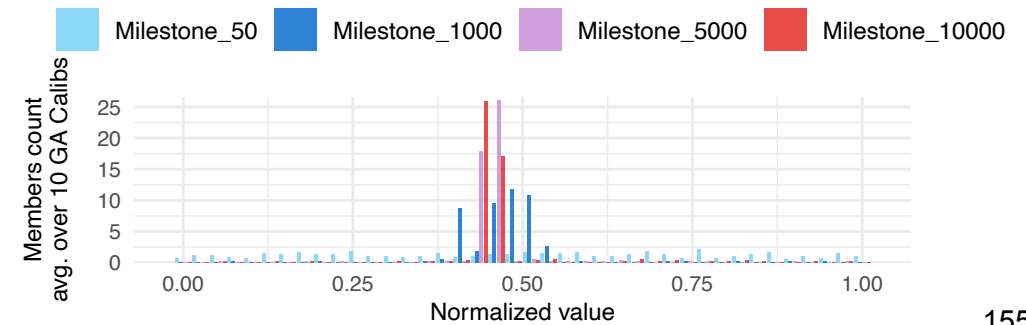
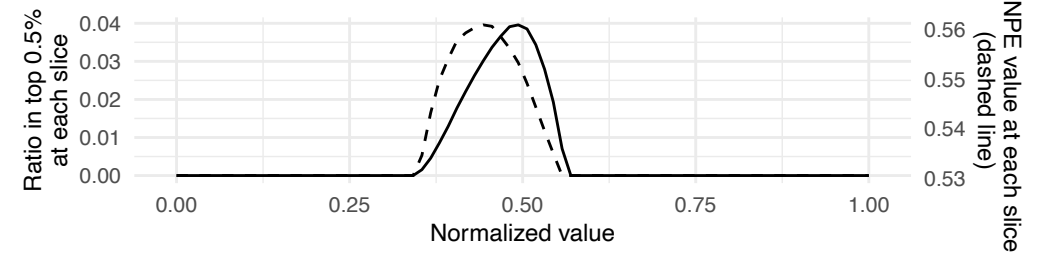
LP



CFR

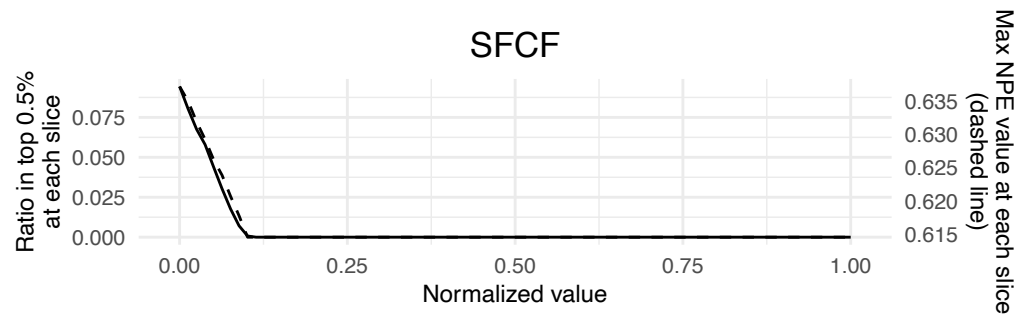


PERC

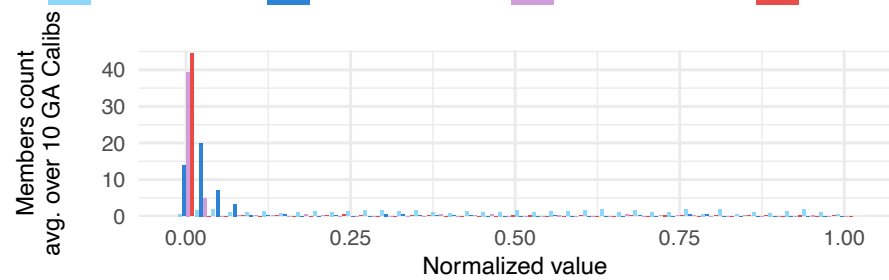


2403_4D_K: 4D Coverage & NPE Profiles

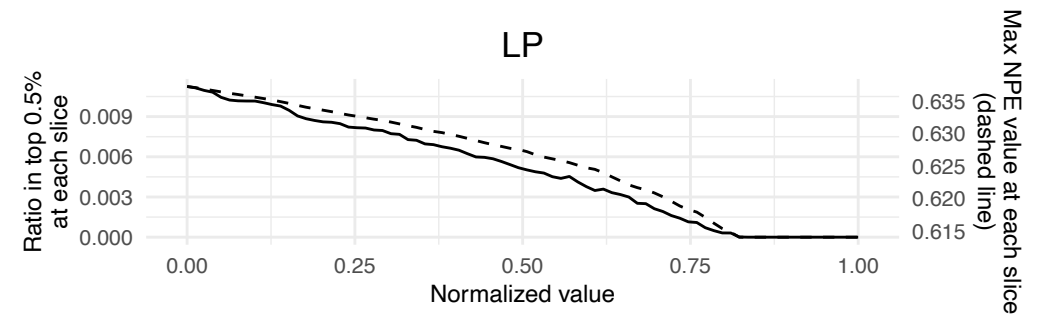
SFCF



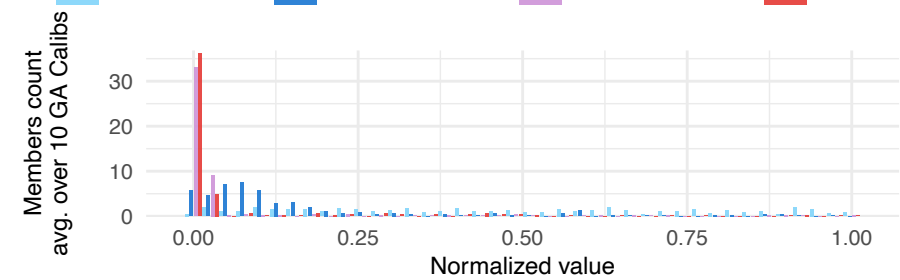
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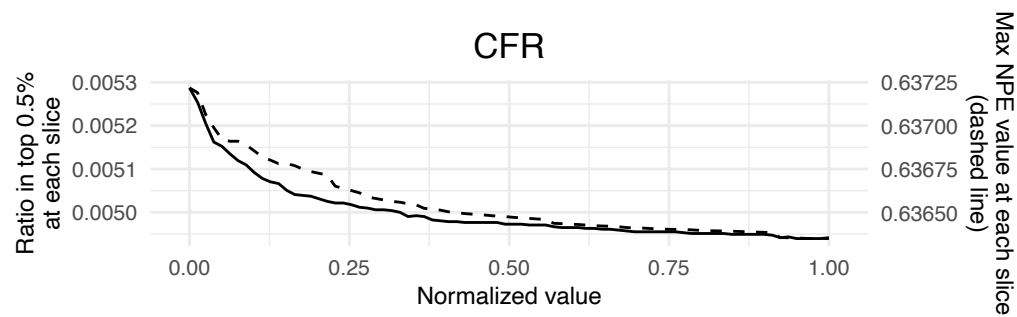
LP



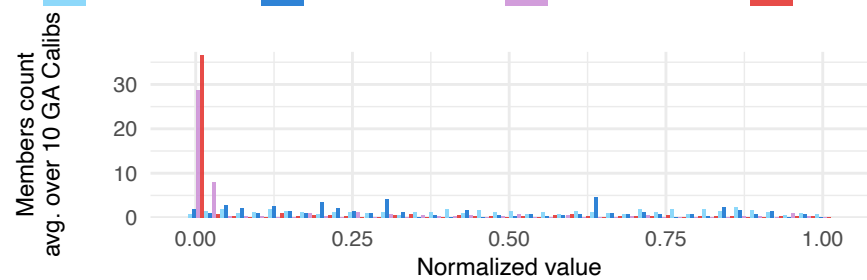
Milestone_50 Milestone_1000 Milestone_5000 Milestone_10000



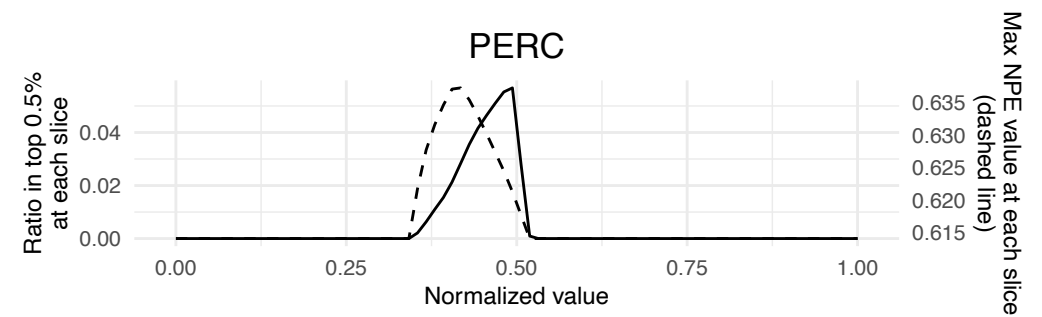
CFR



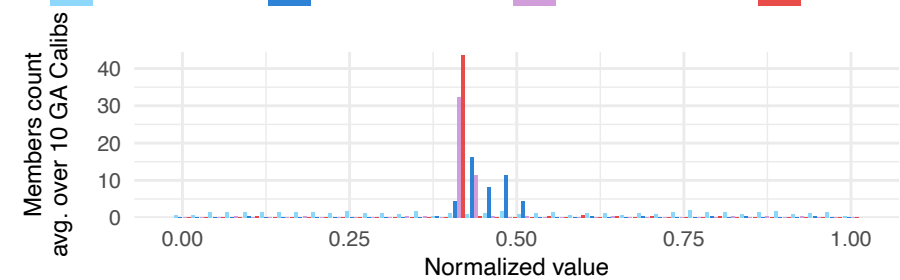
Milestone_50 Milestone_1000 Milestone_5000 Milestone_10000



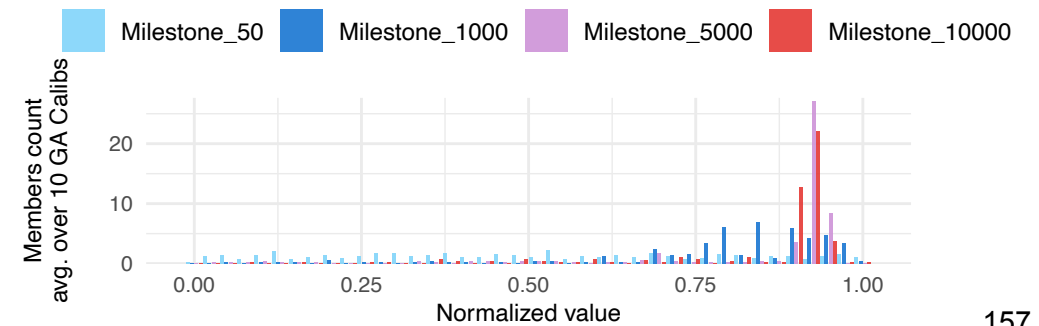
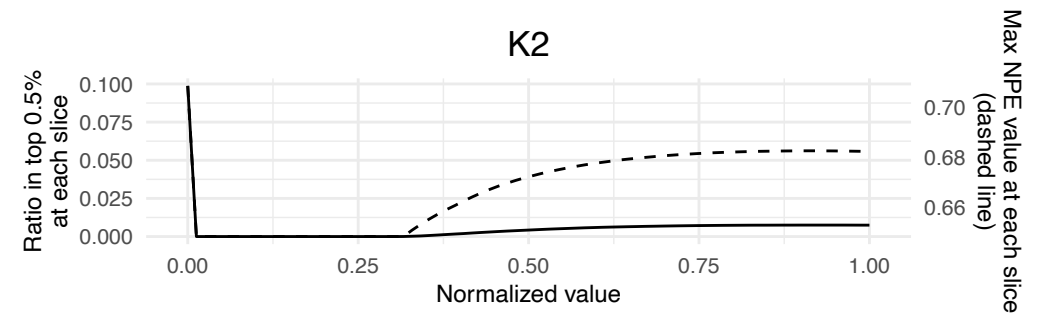
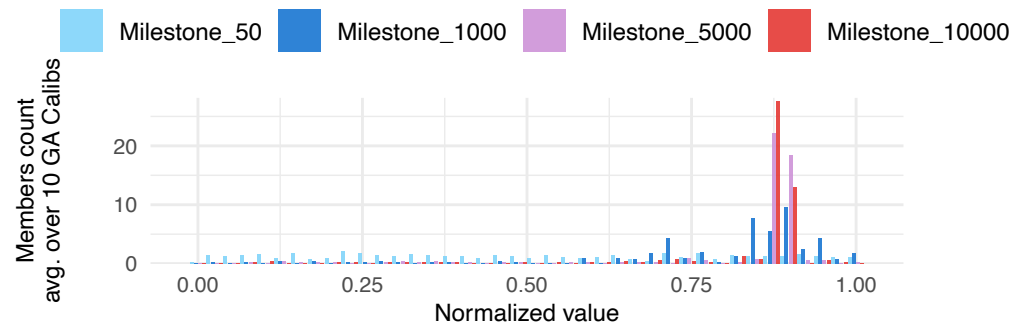
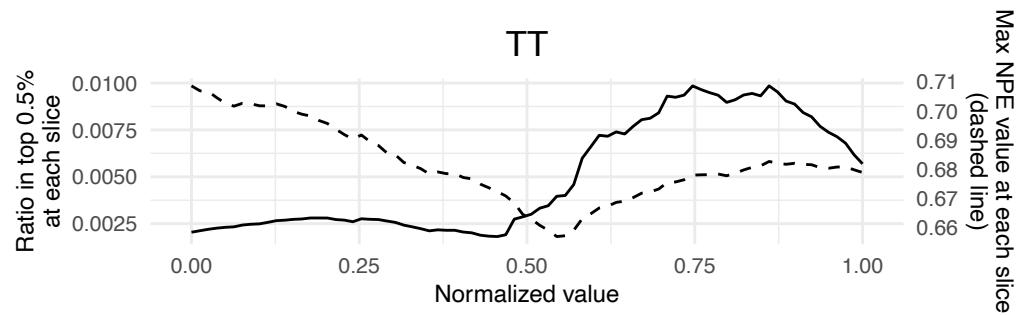
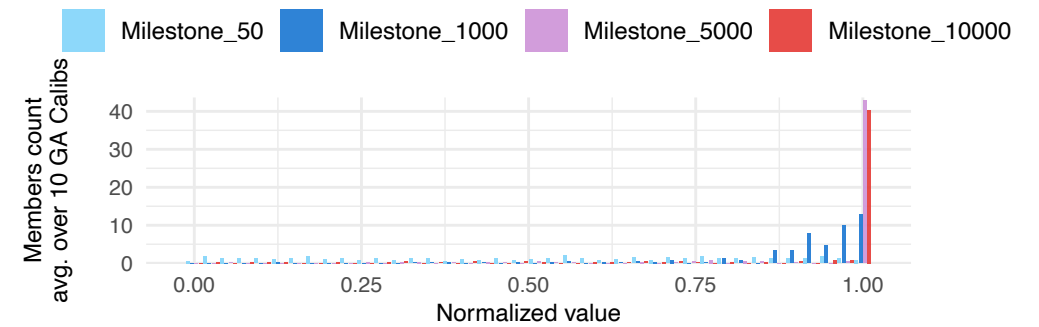
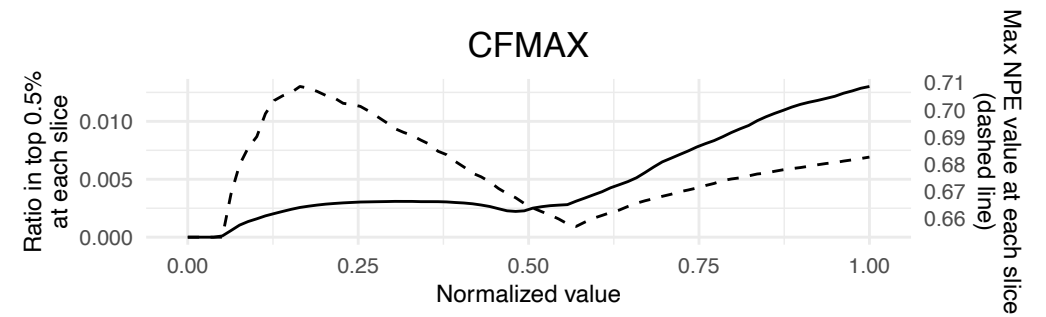
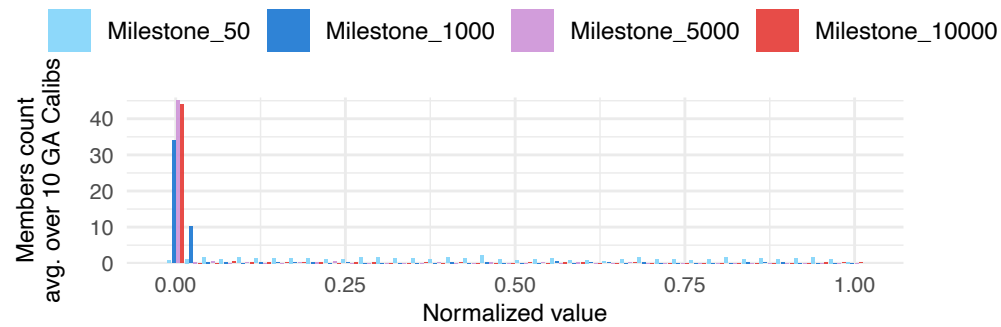
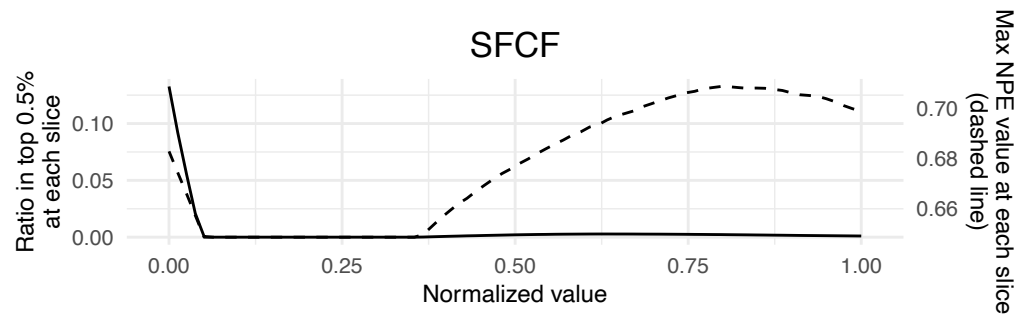
PERC



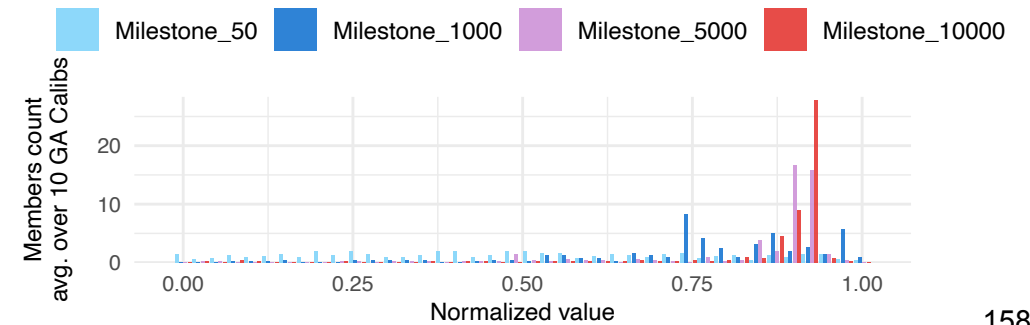
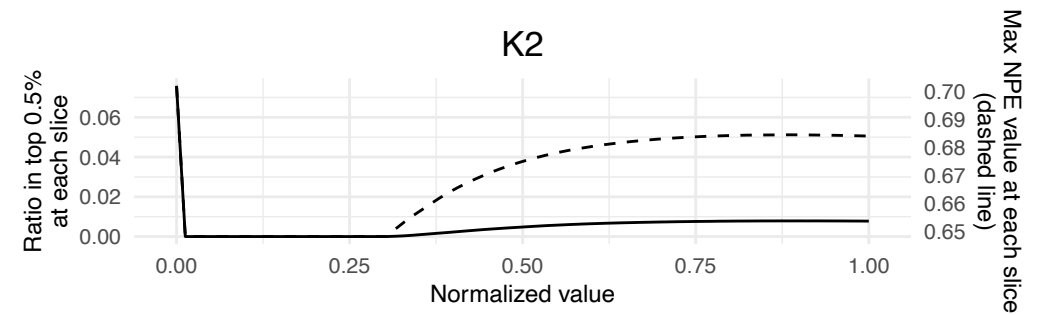
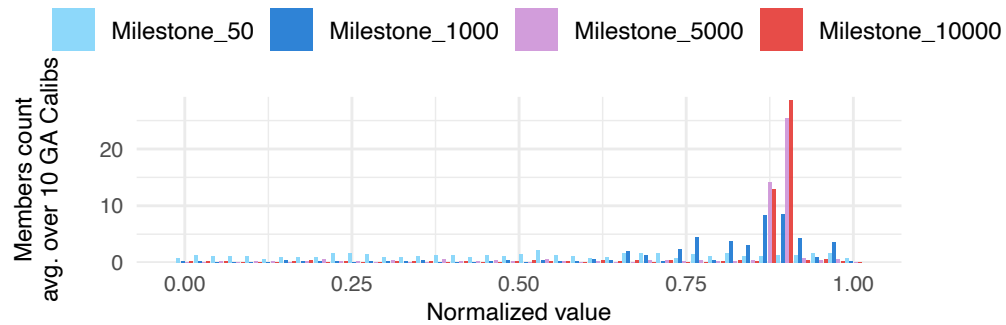
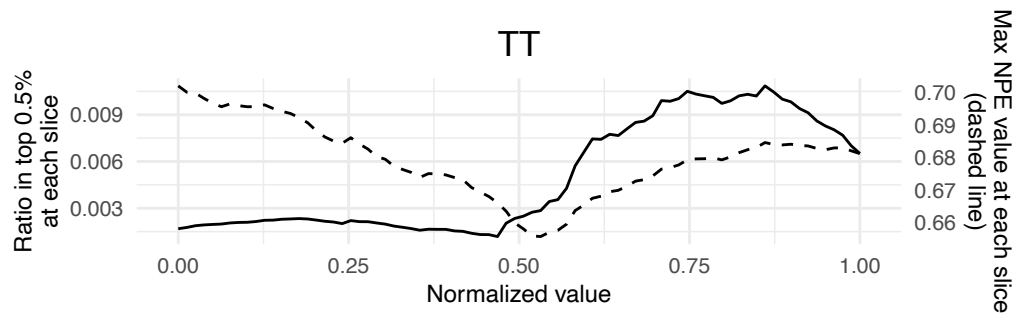
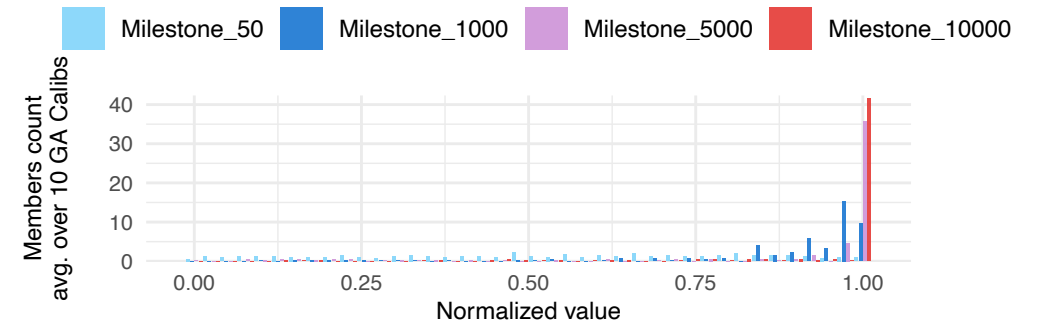
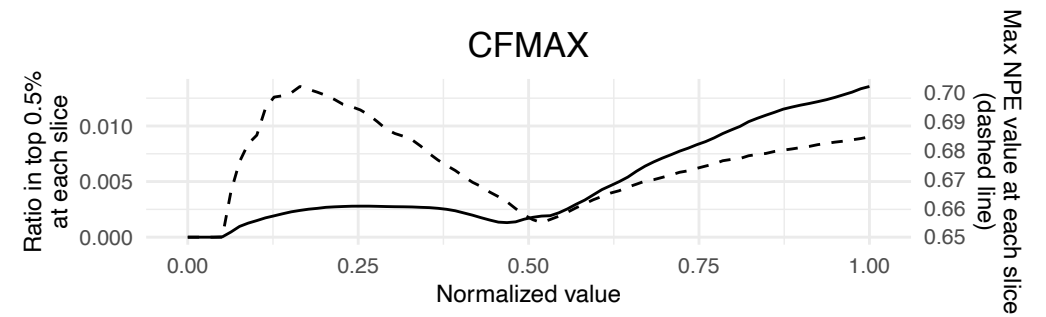
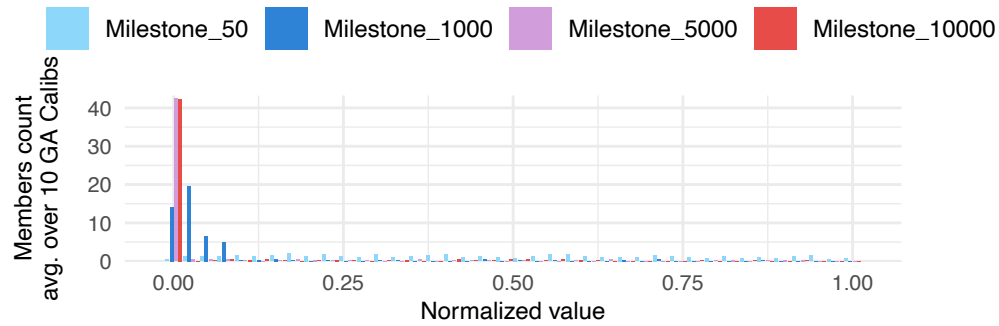
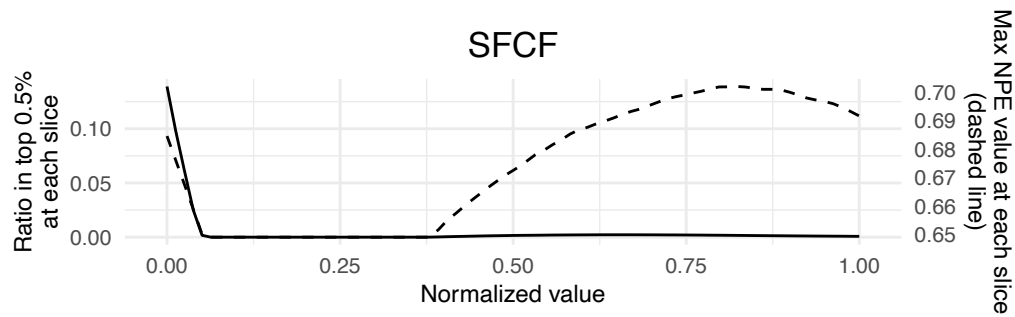
Milestone_50 Milestone_1000 Milestone_5000 Milestone_10000



2426_4D_A: 4D Coverage & NPE Profiles

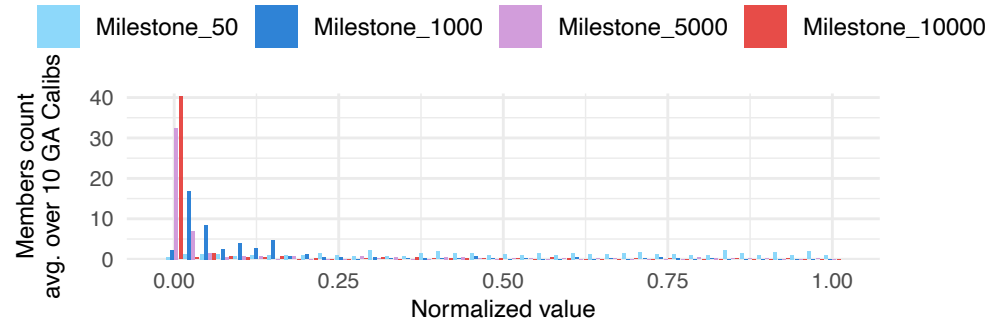
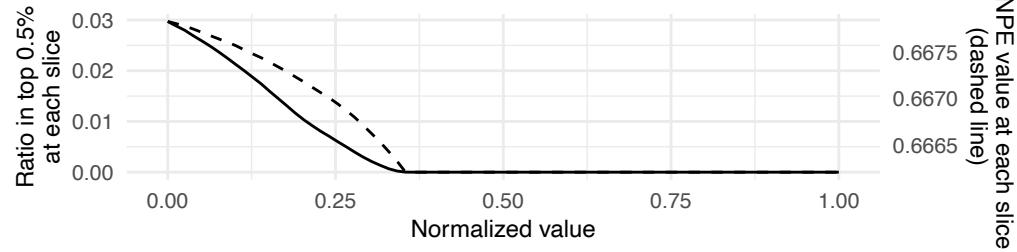


2426_4D_B: 4D Coverage & NPE Profiles

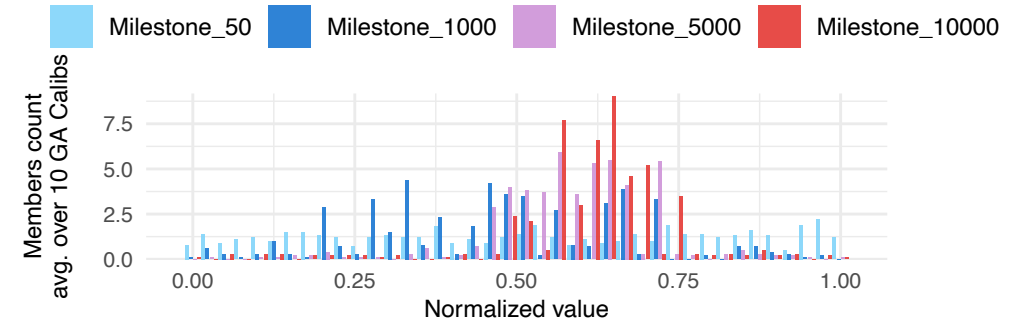
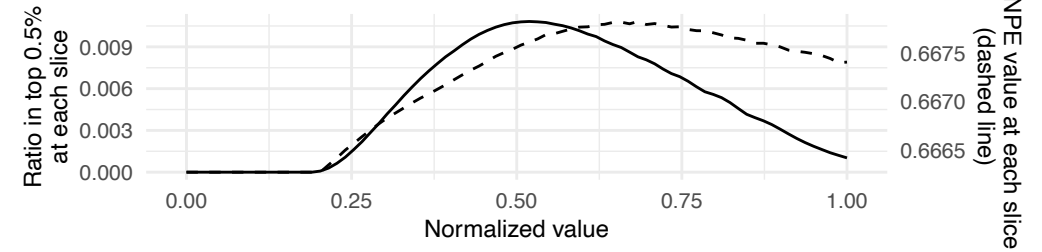


2426_4D_D: 4D Coverage & NPE Profiles

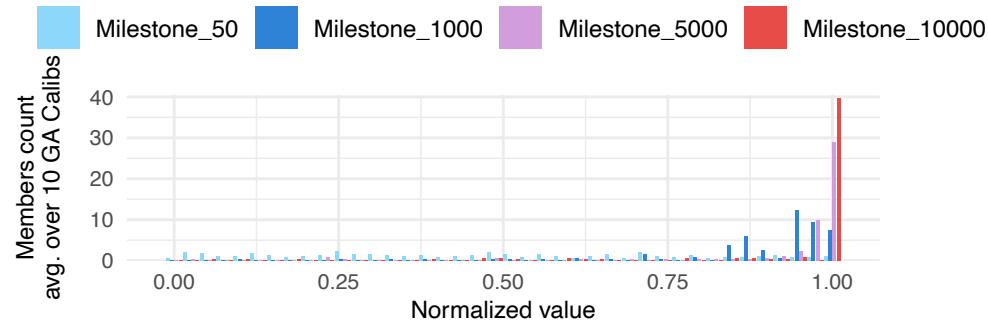
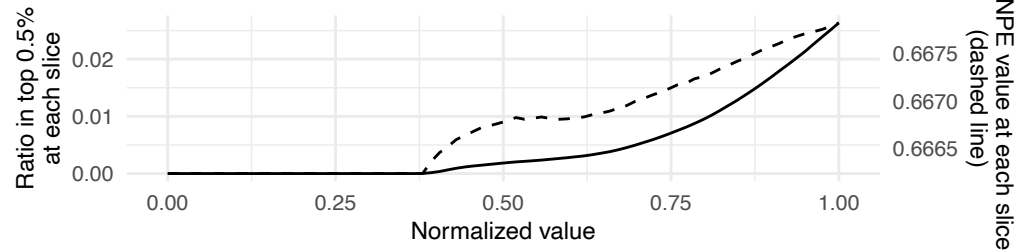
LP



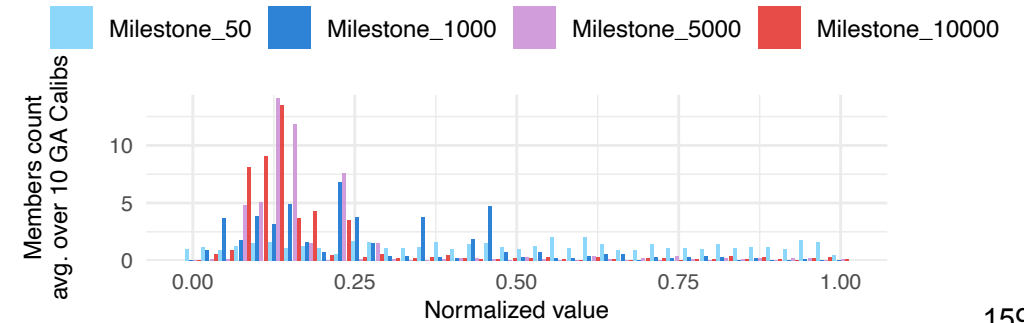
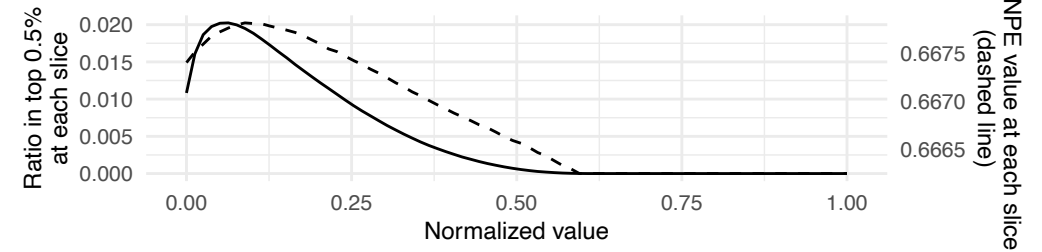
Alpha



PERC

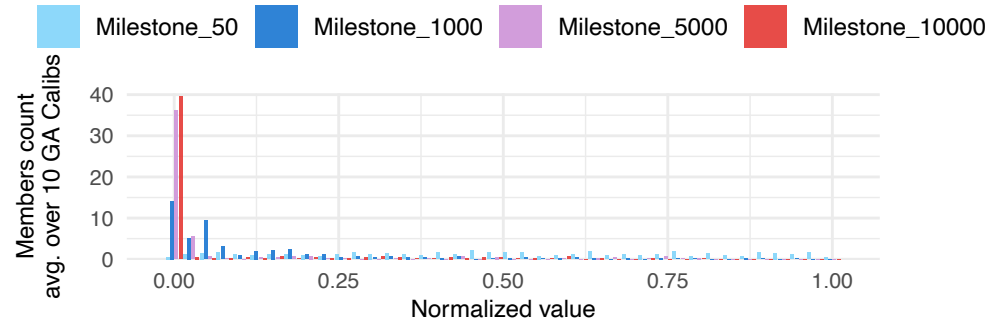
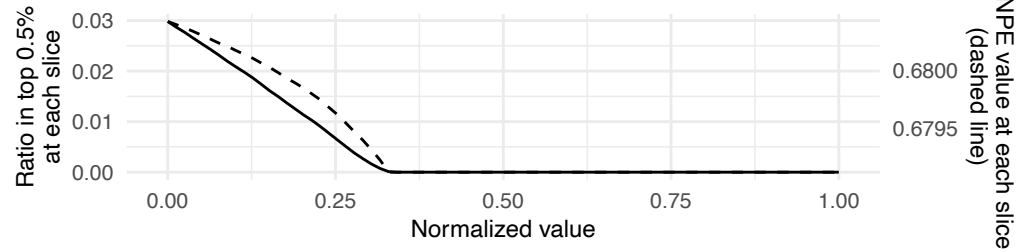


K1

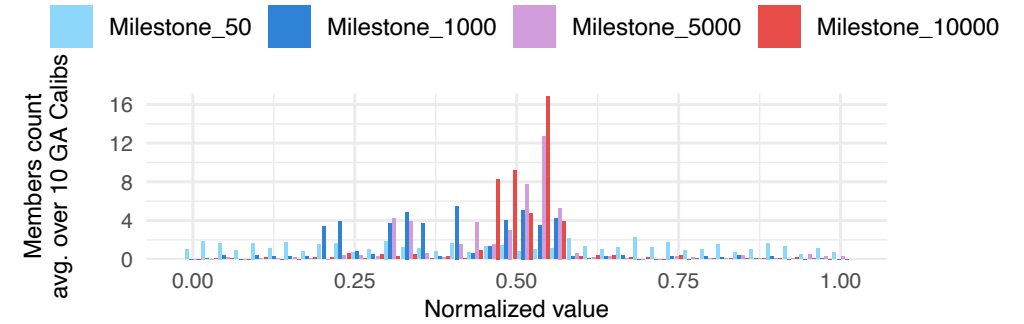
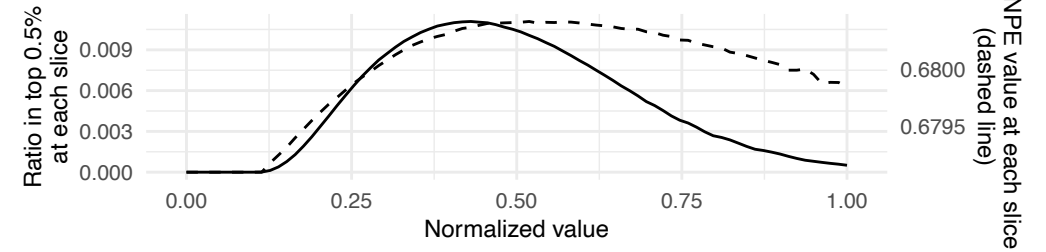


2426_4D_E: 4D Coverage & NPE Profiles

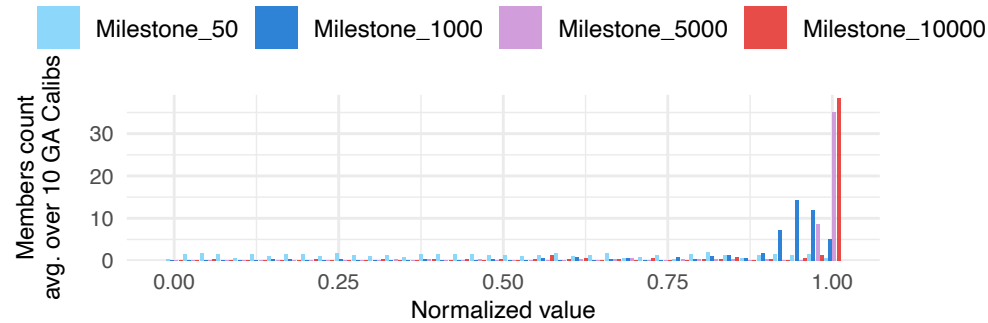
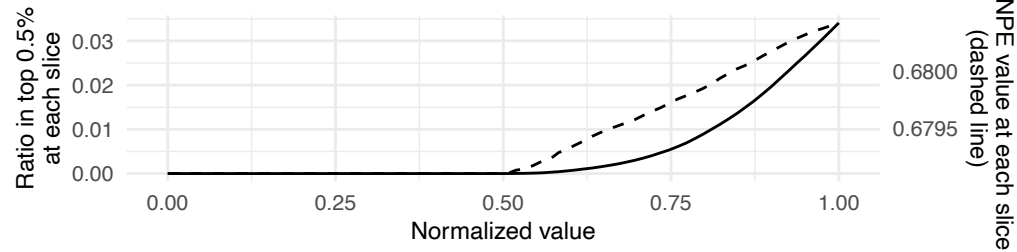
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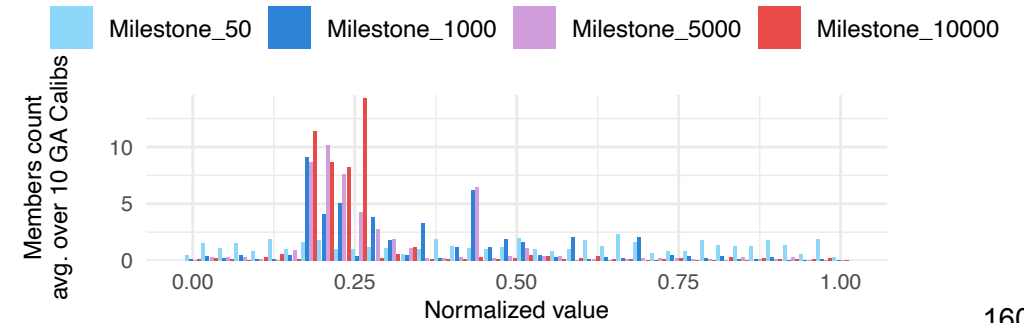
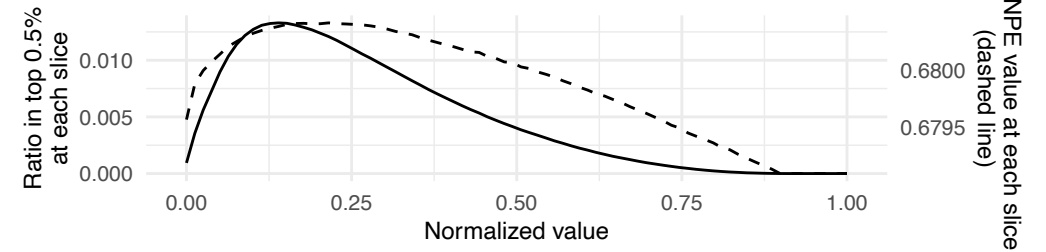
Alpha



PERC

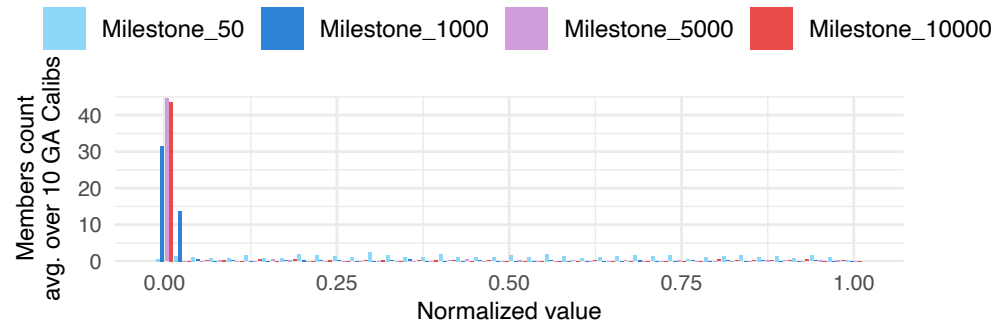
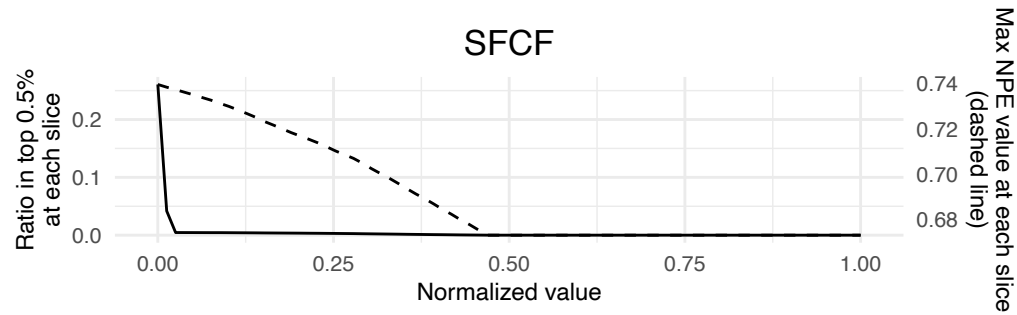


K1

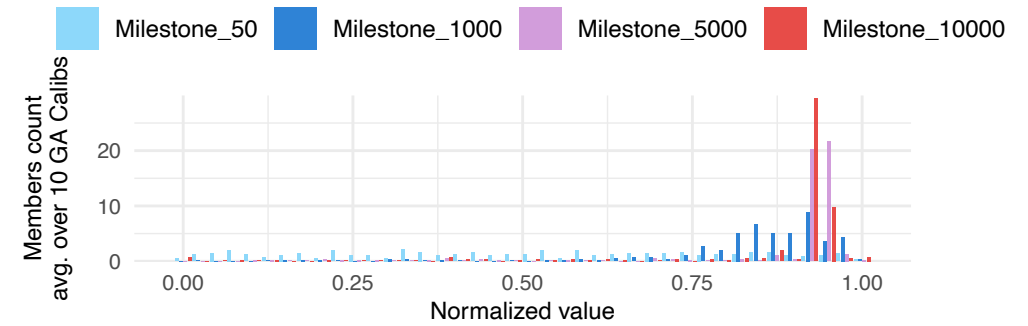
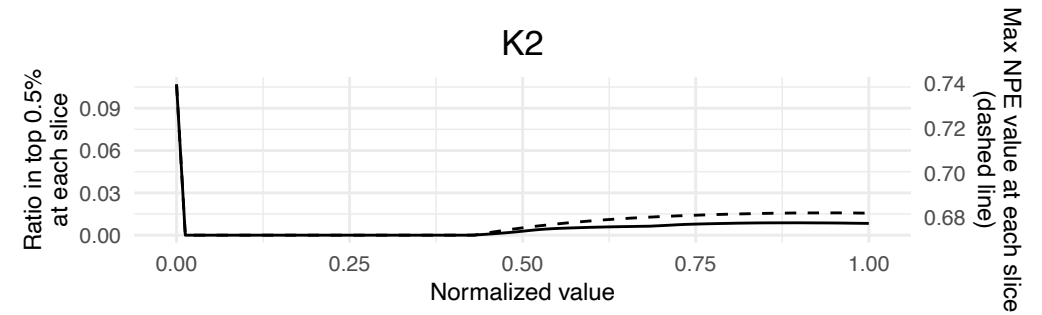


2426_4D_J: 4D Coverage & NPE Profiles

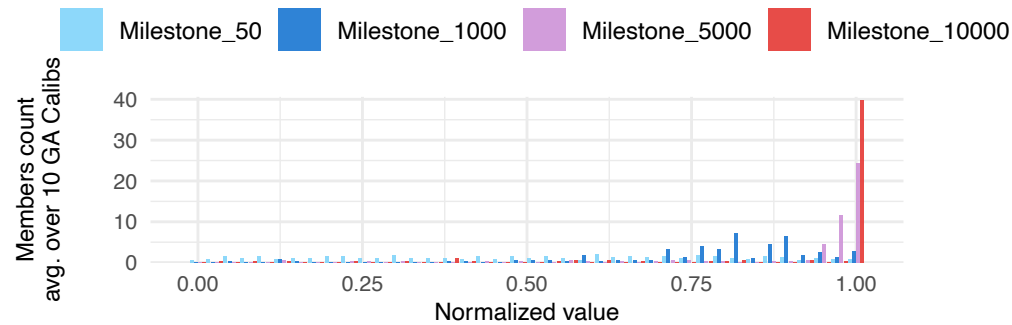
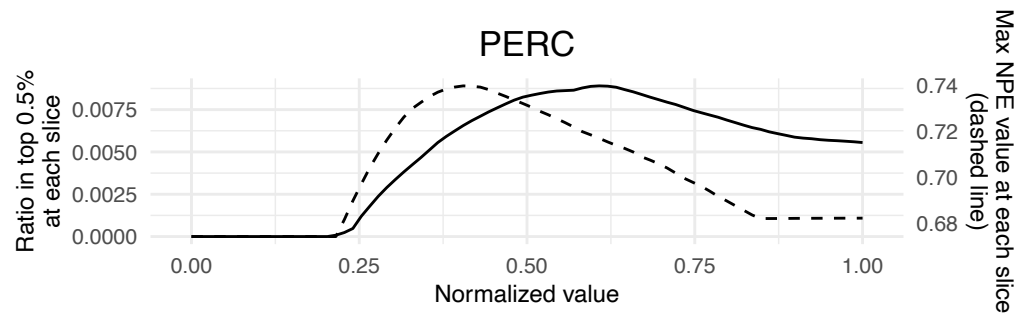
SFCF



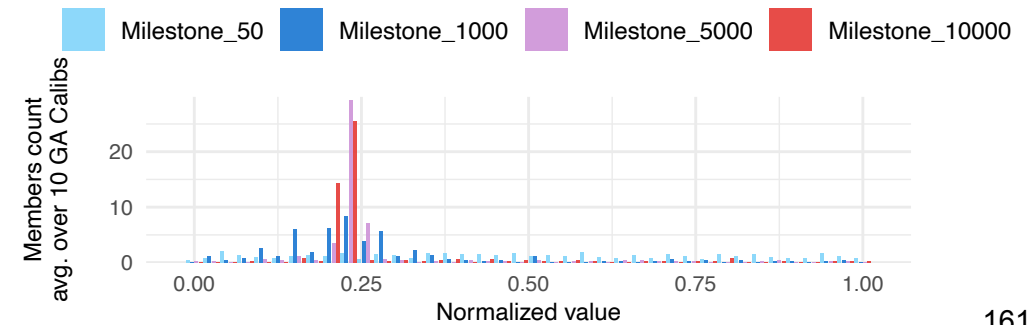
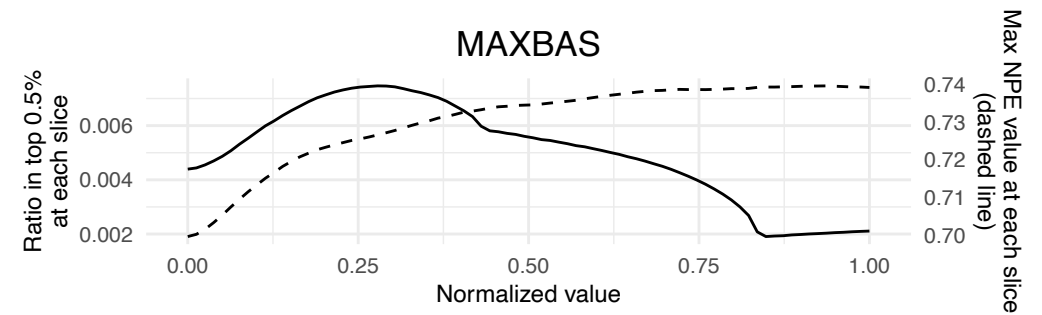
K2



PERC

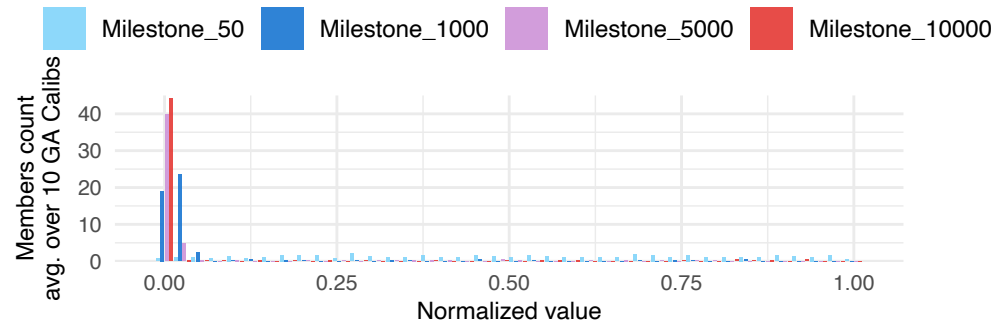
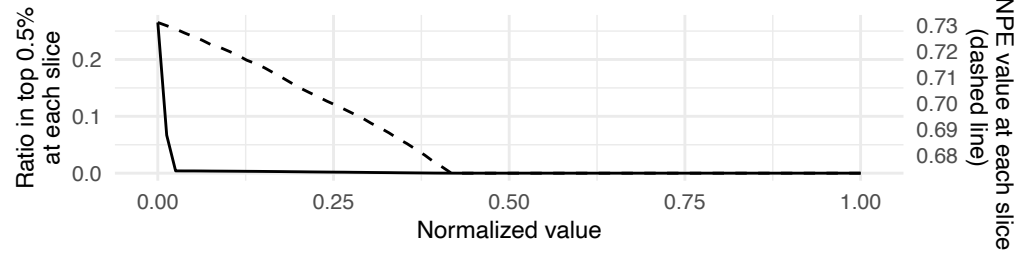


MAXBAS

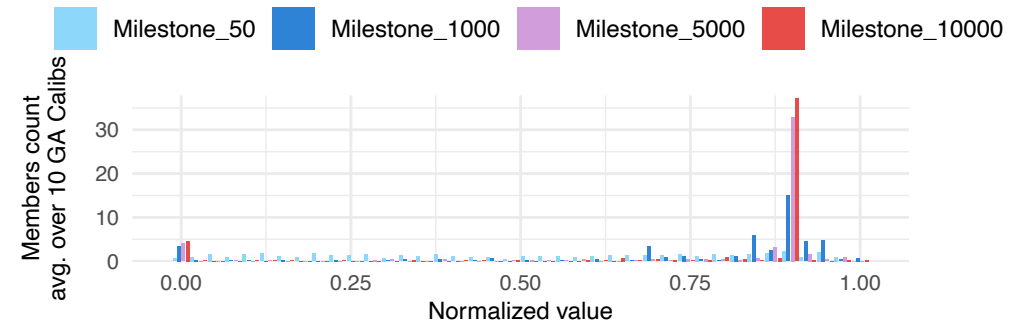
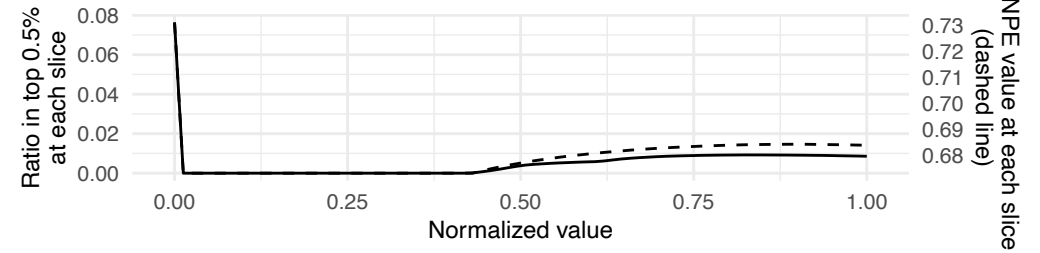


2426_4D_K: 4D Coverage & NPE Profiles

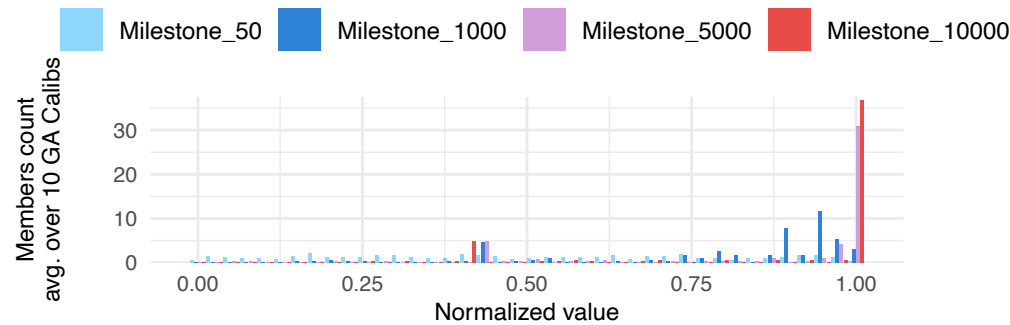
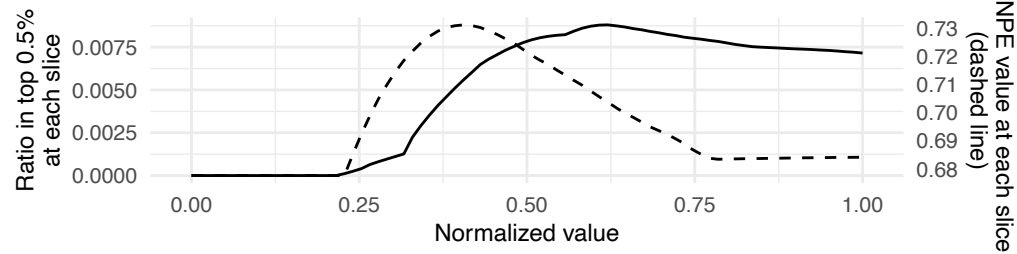
SFCF



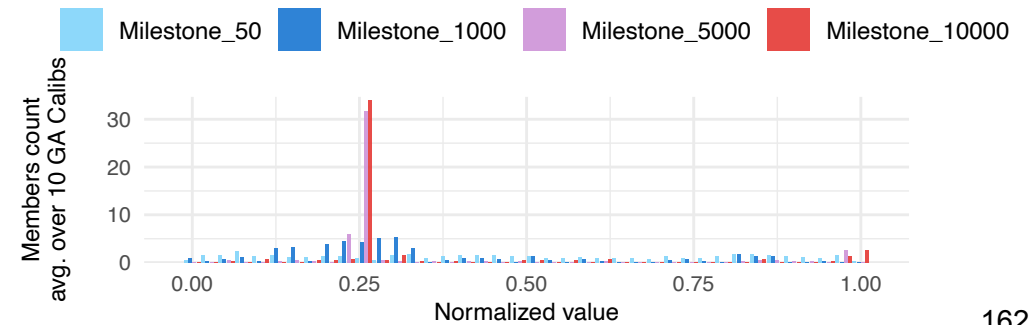
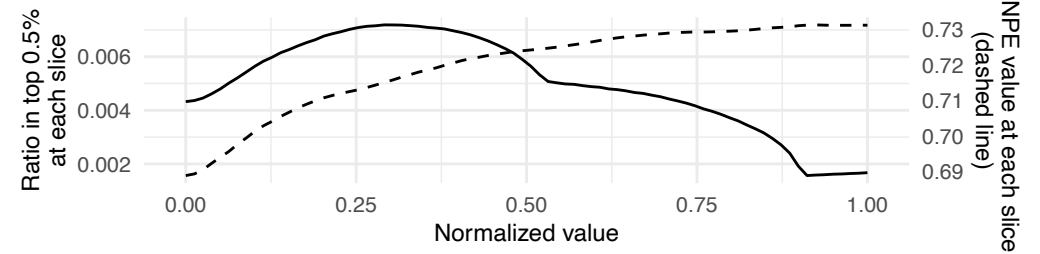
K2



PERC

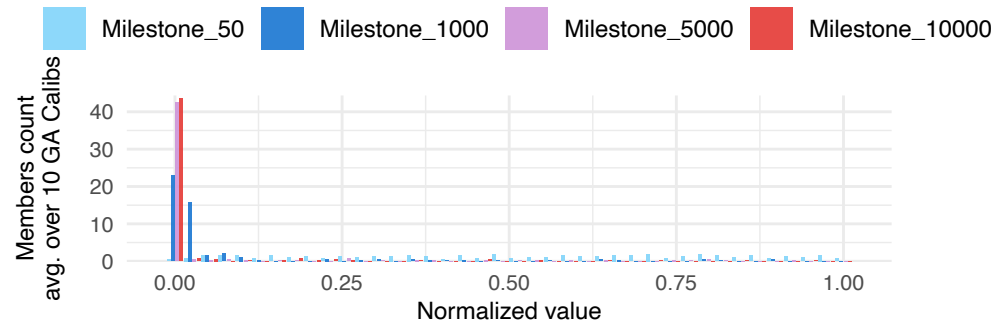
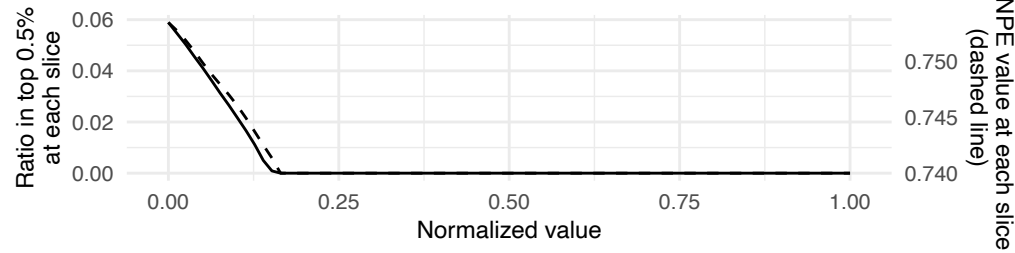


MAXBAS

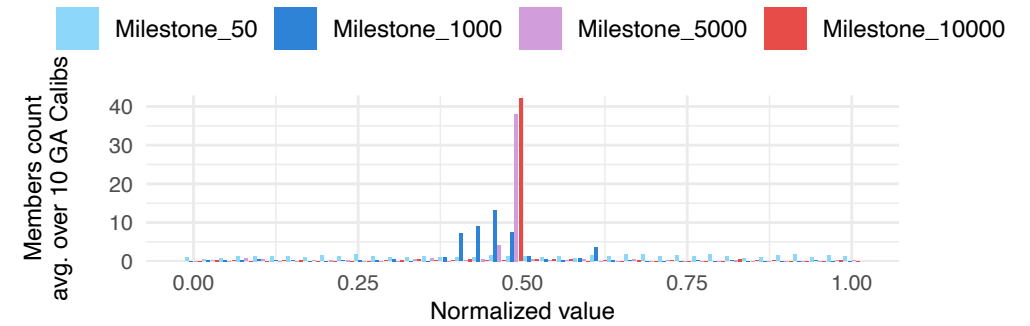
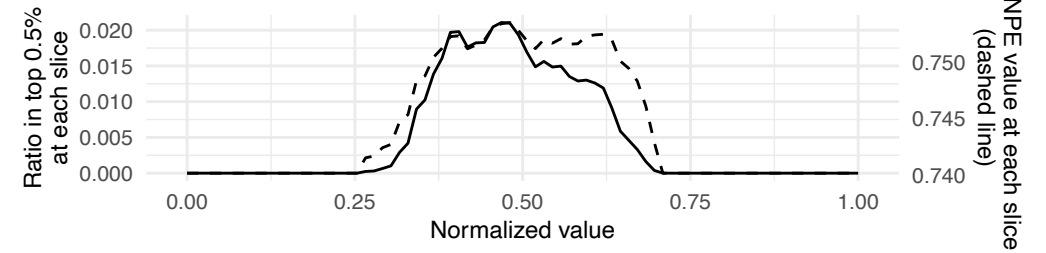


5014_4D_A: 4D Coverage & NPE Profiles

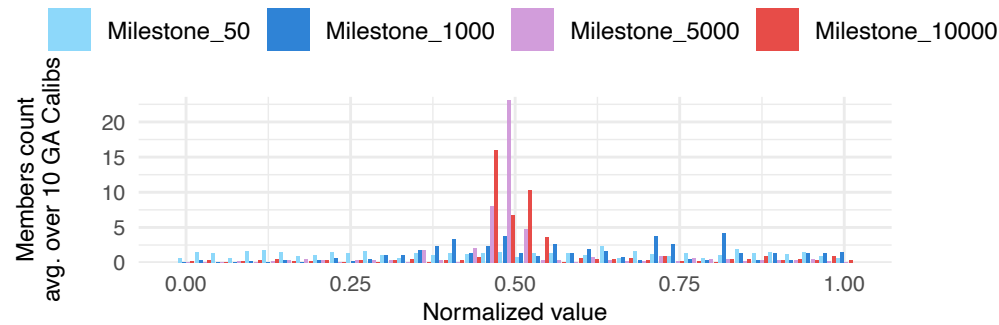
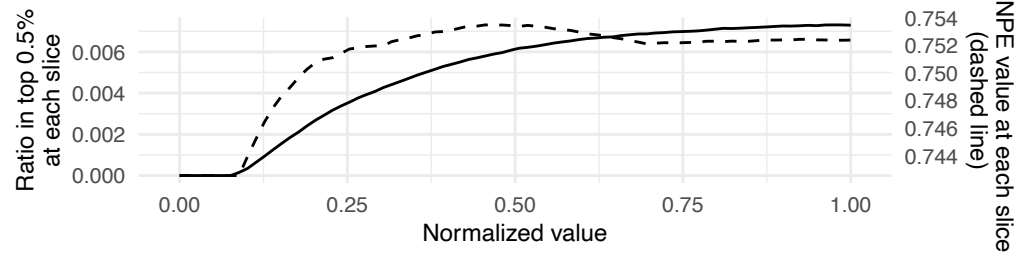
SFCF



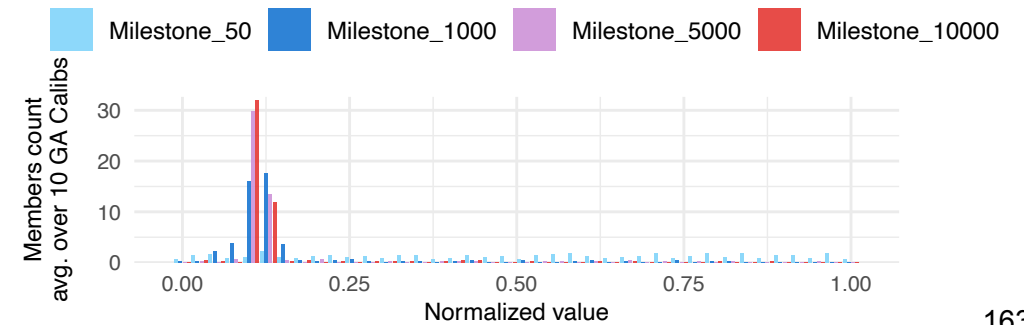
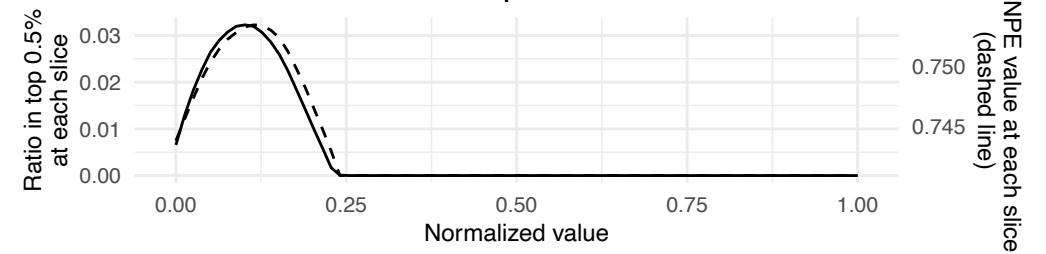
TT



CFMAX

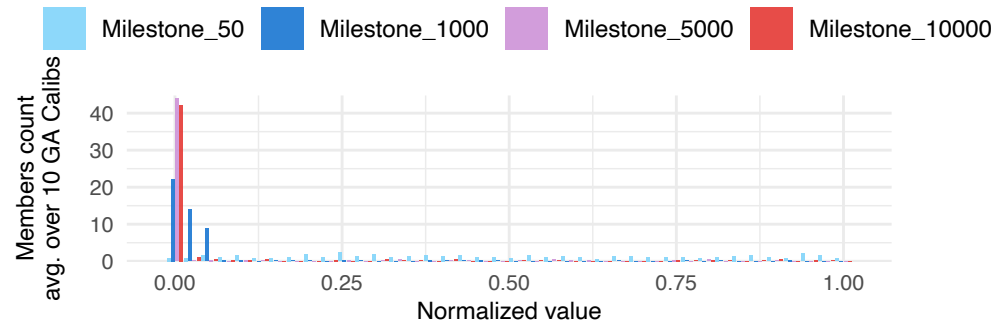
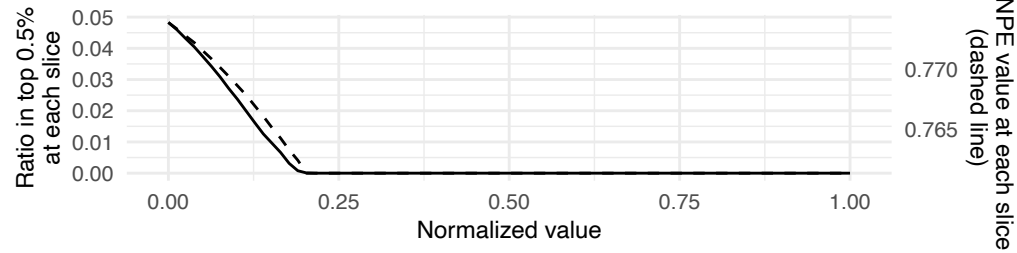


Alpha

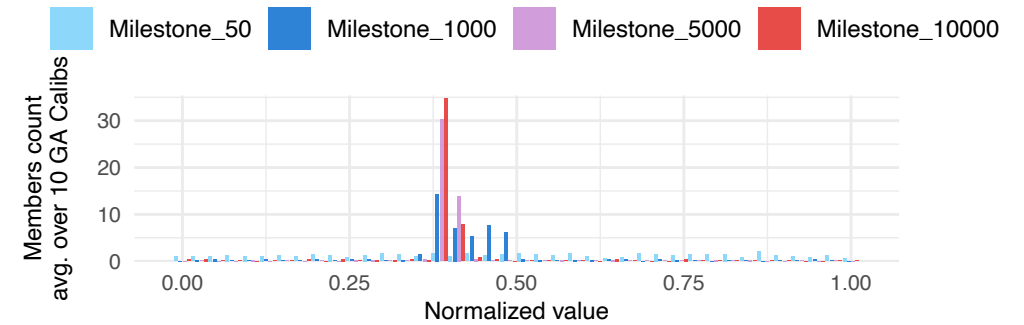
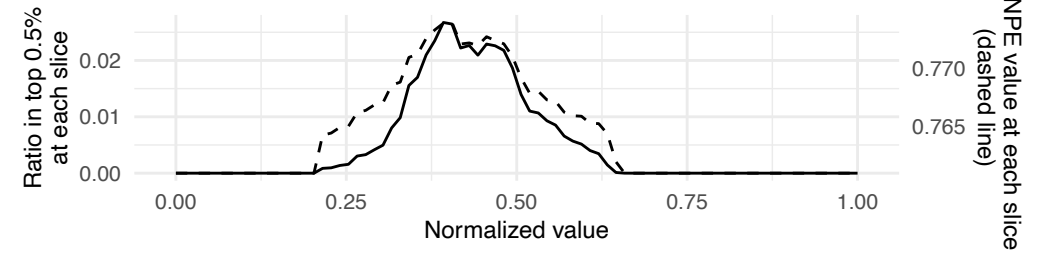


5014_4D_B: 4D Coverage & NPE Profiles

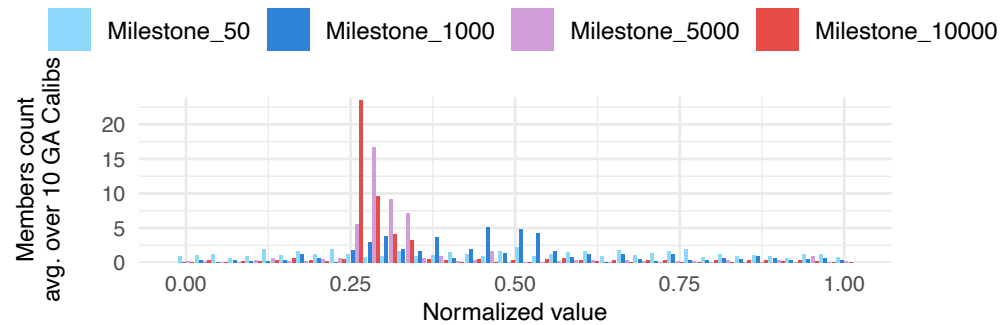
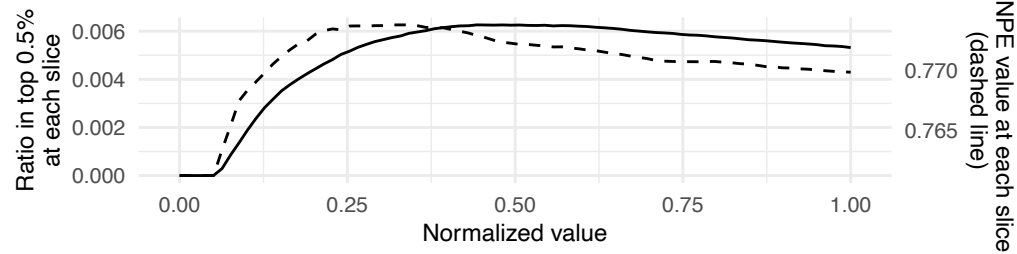
SFCF



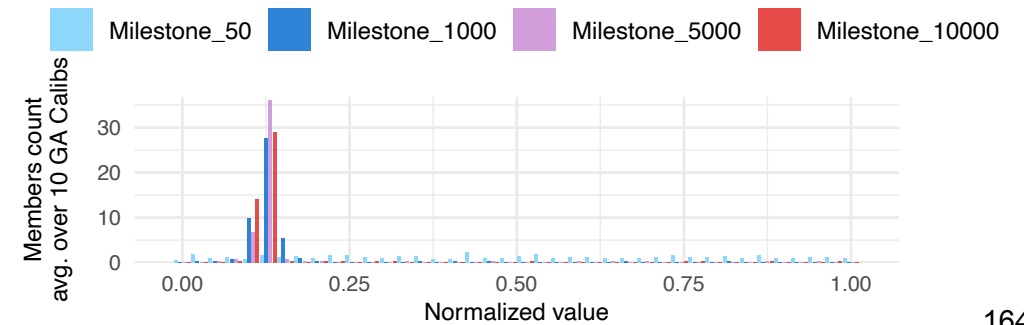
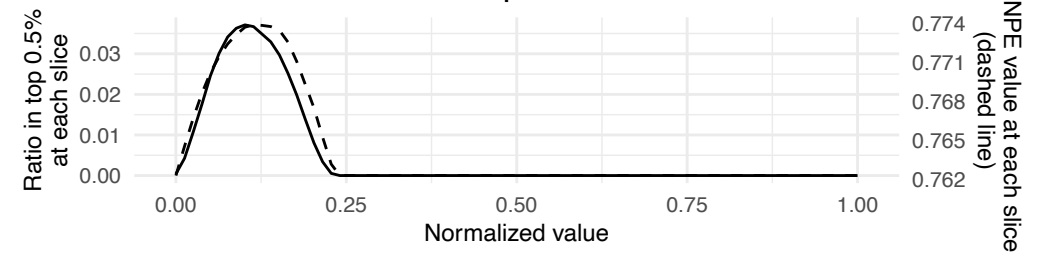
TT



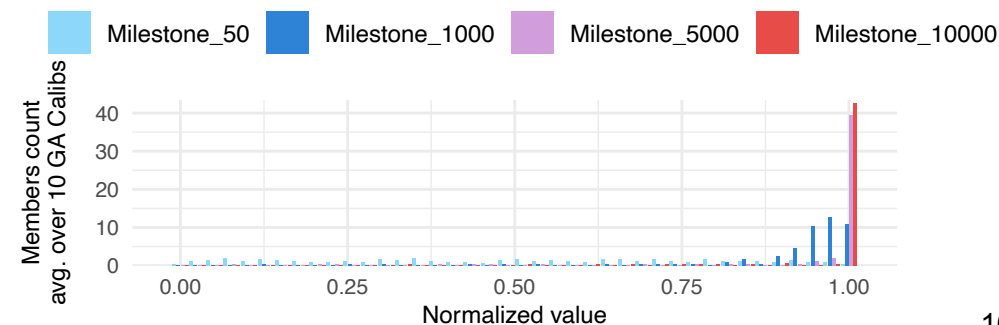
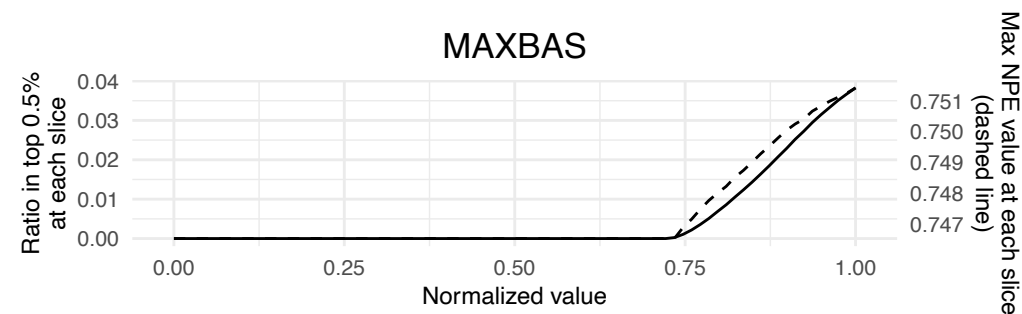
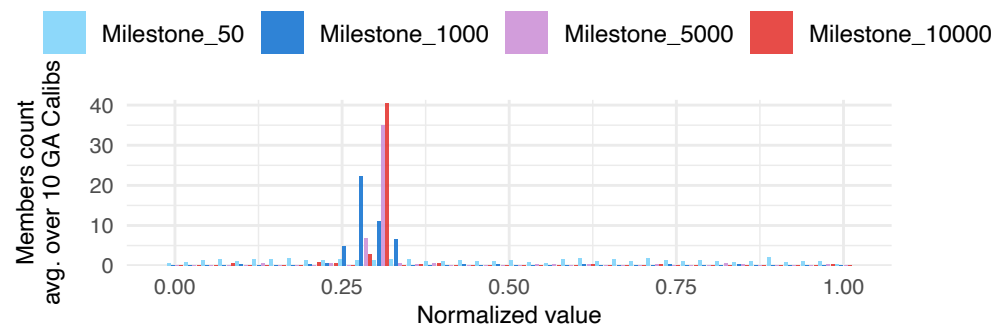
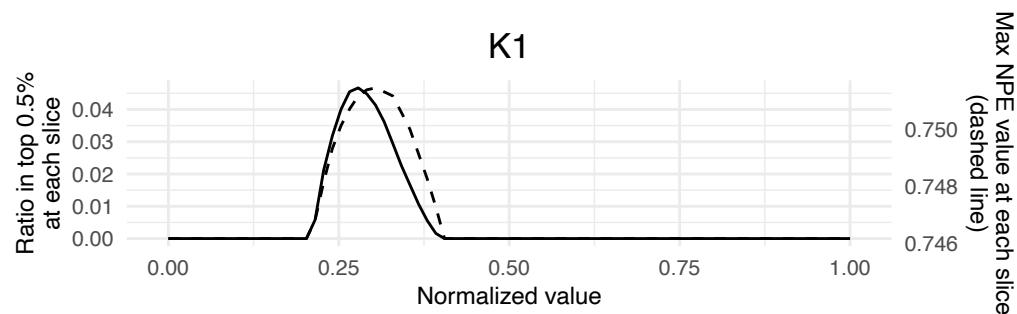
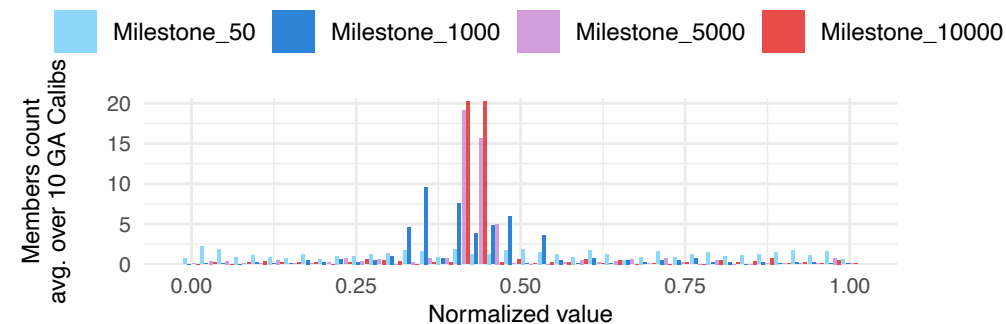
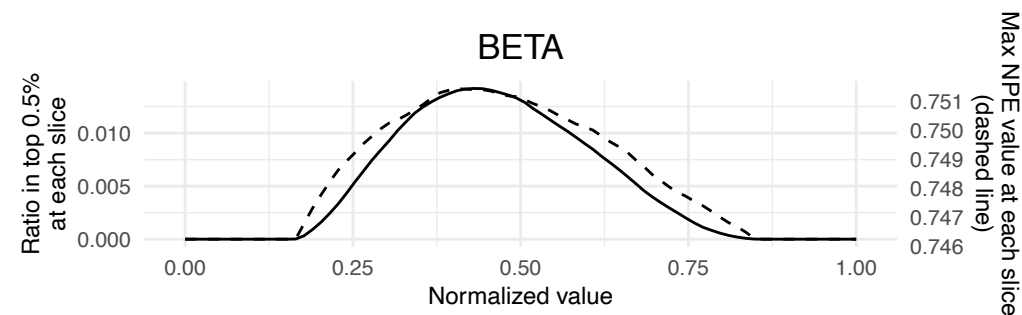
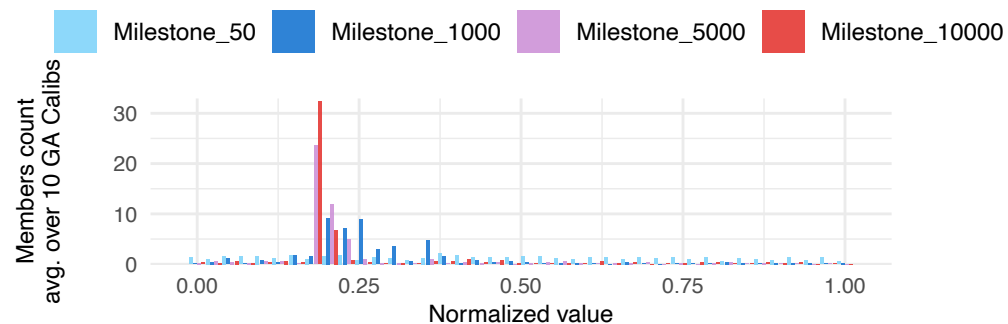
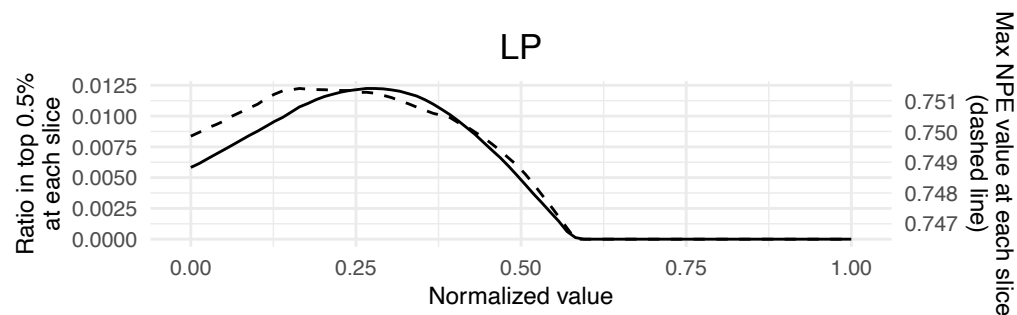
CFMAX



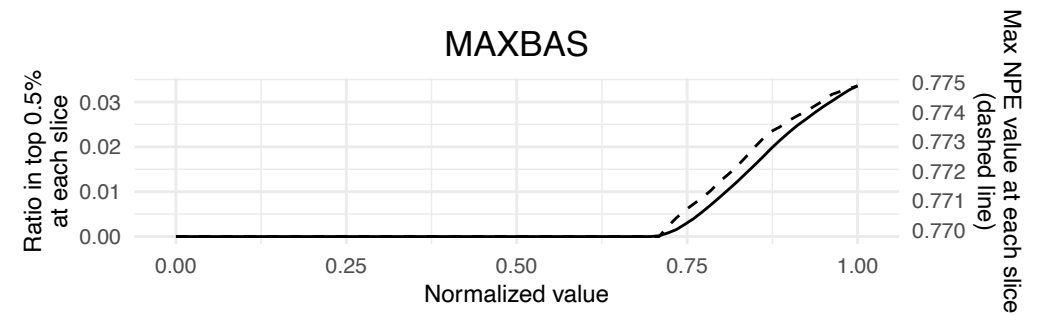
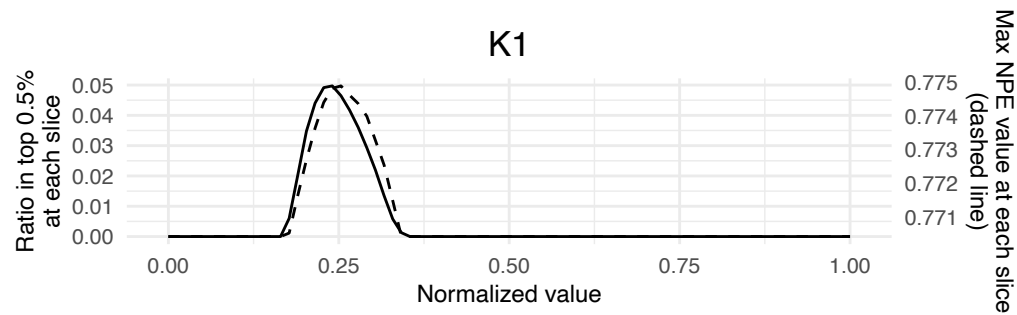
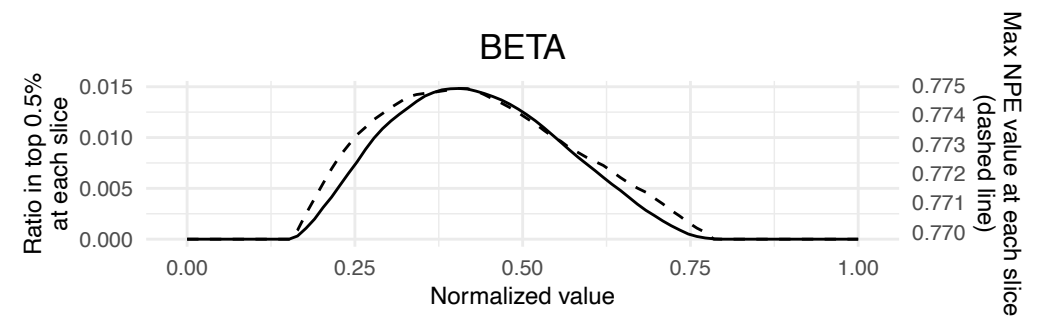
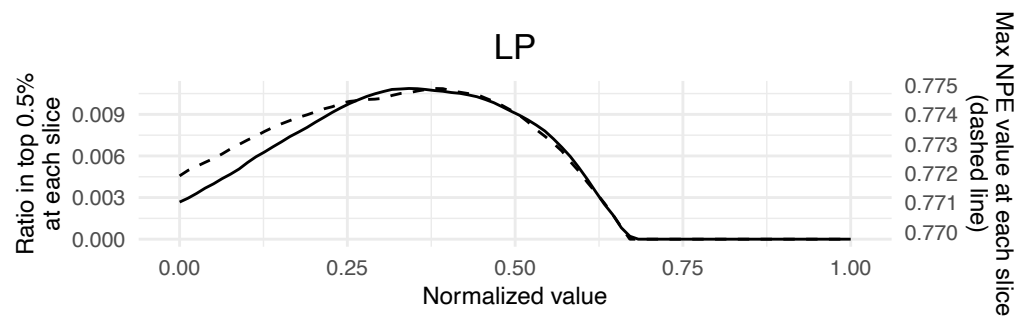
Alpha



5014_4D_D: 4D Coverage & NPE Profiles

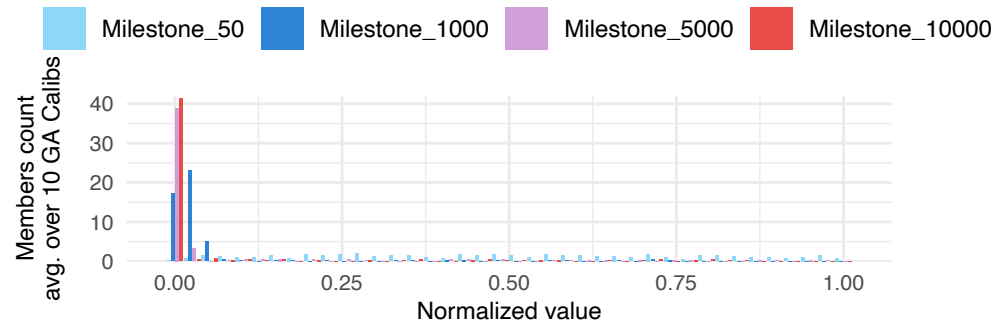
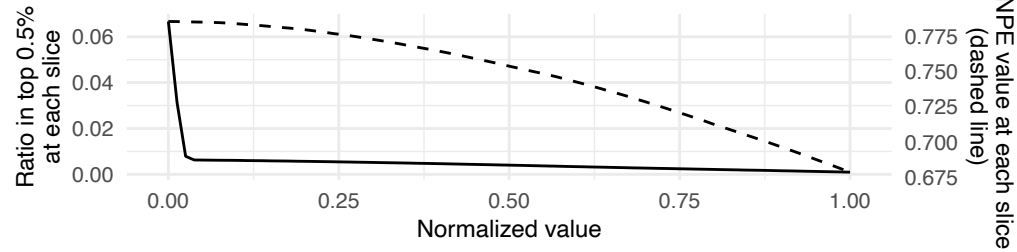


5014_4D_E: 4D Coverage & NPE Profiles

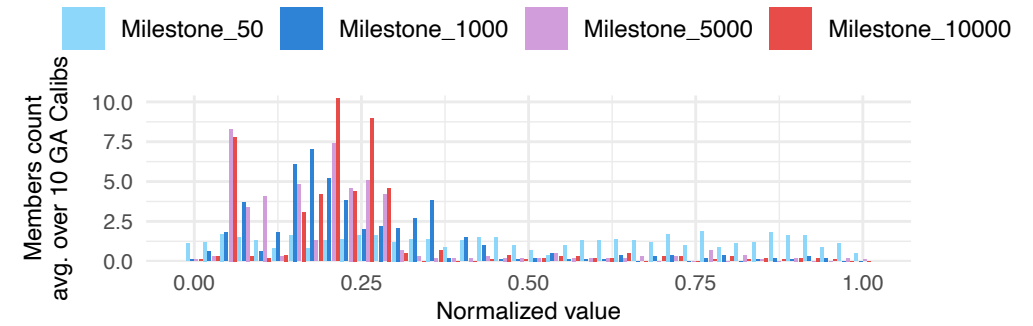
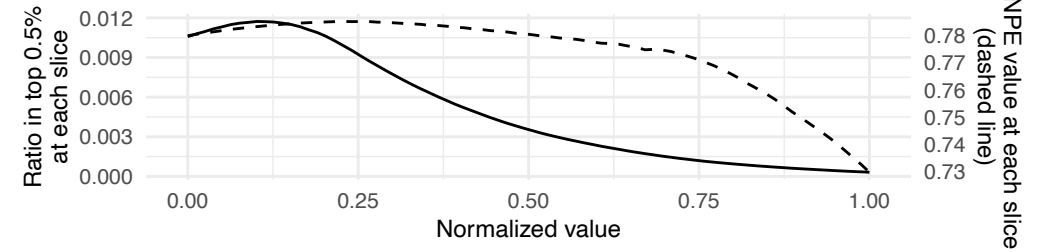


5014_4D_J: 4D Coverage & NPE Profiles

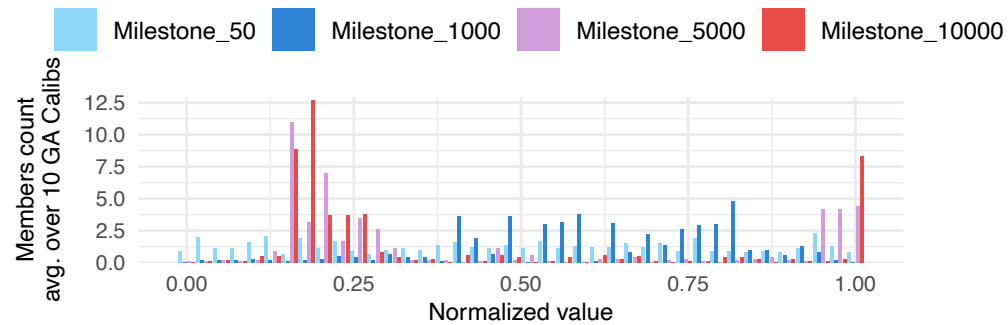
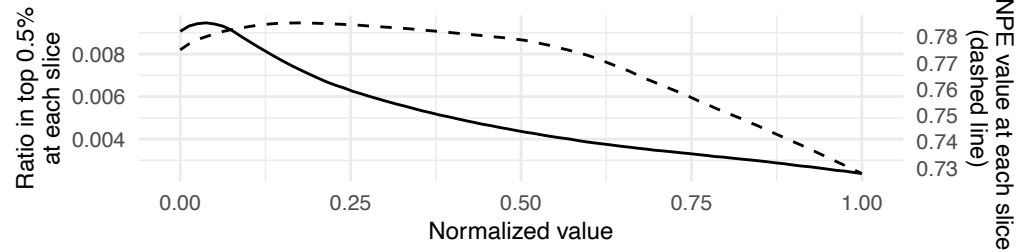
SFCF



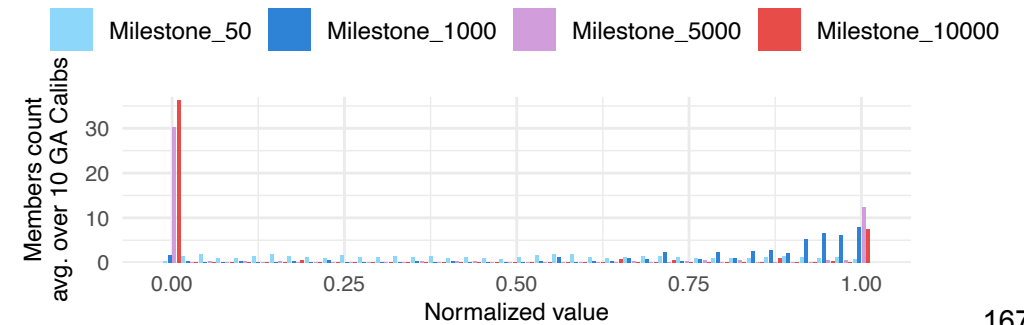
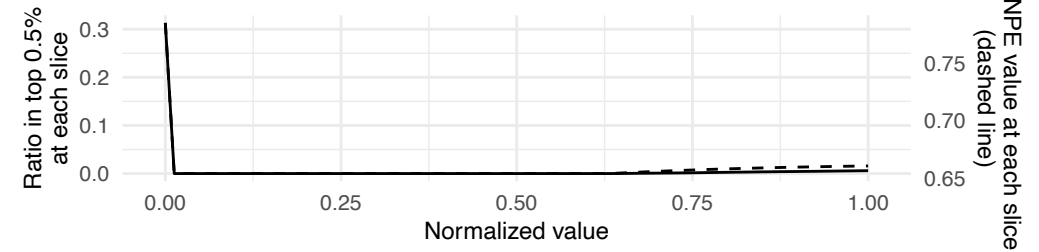
Alpha



K1

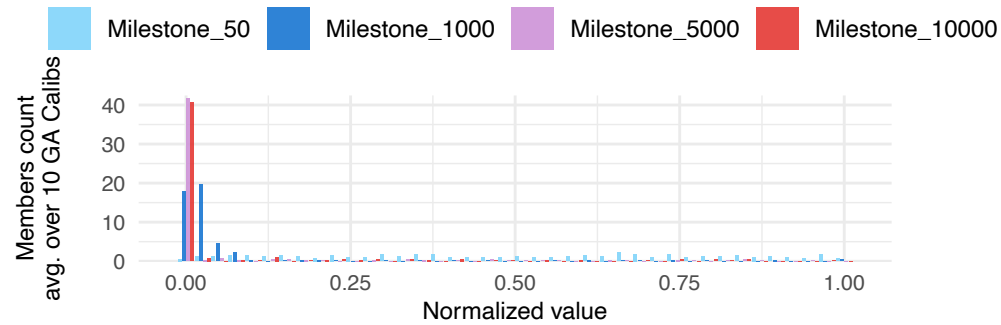
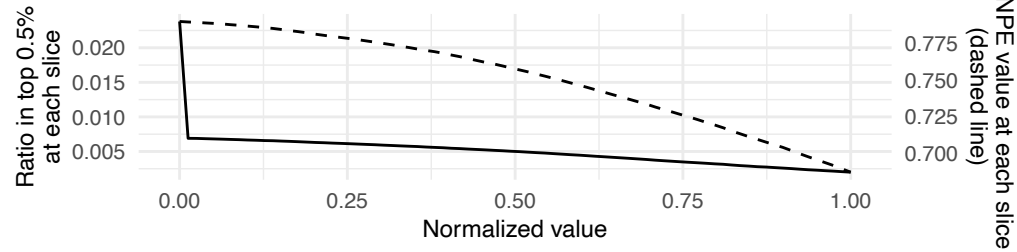


K2

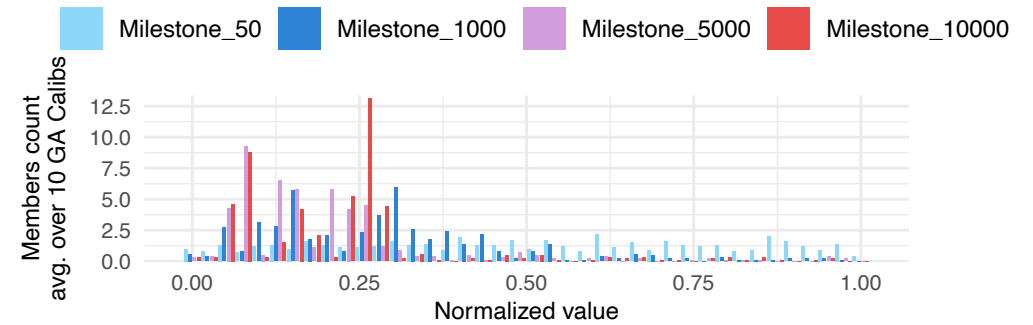
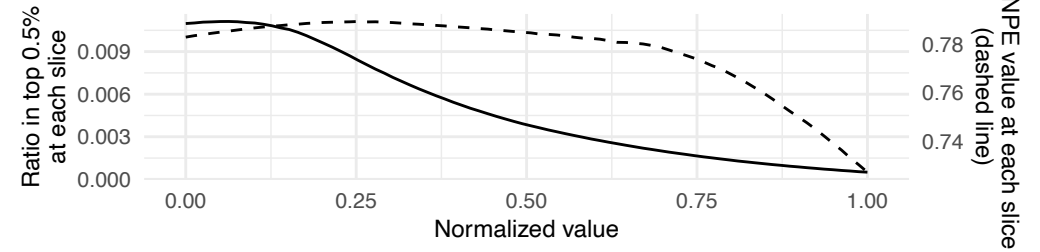


5014_4D_K: 4D Coverage & NPE Profiles

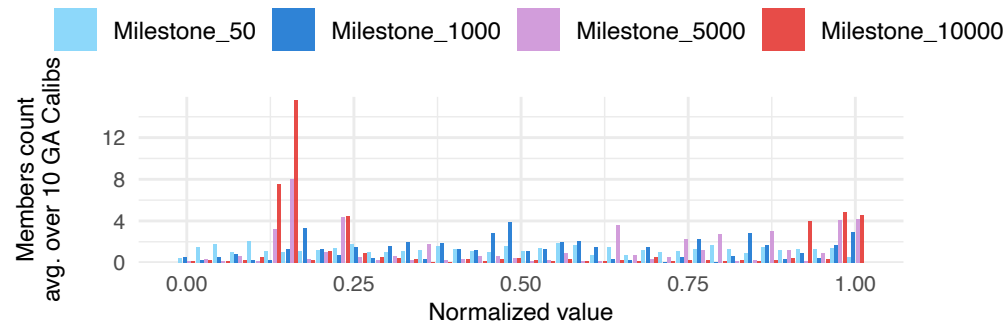
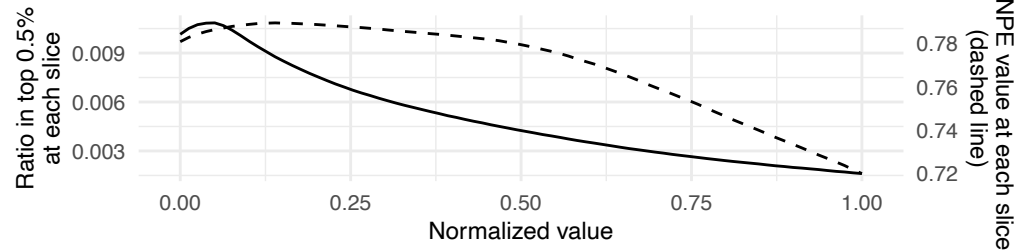
SFCF



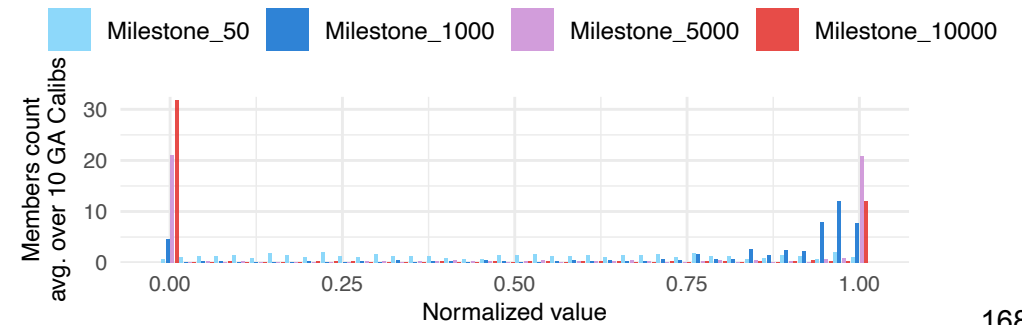
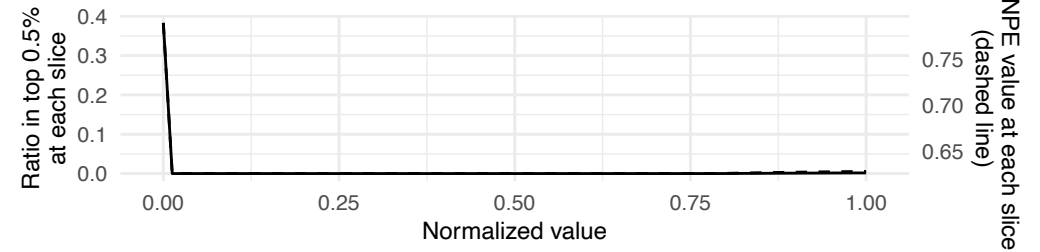
Alpha



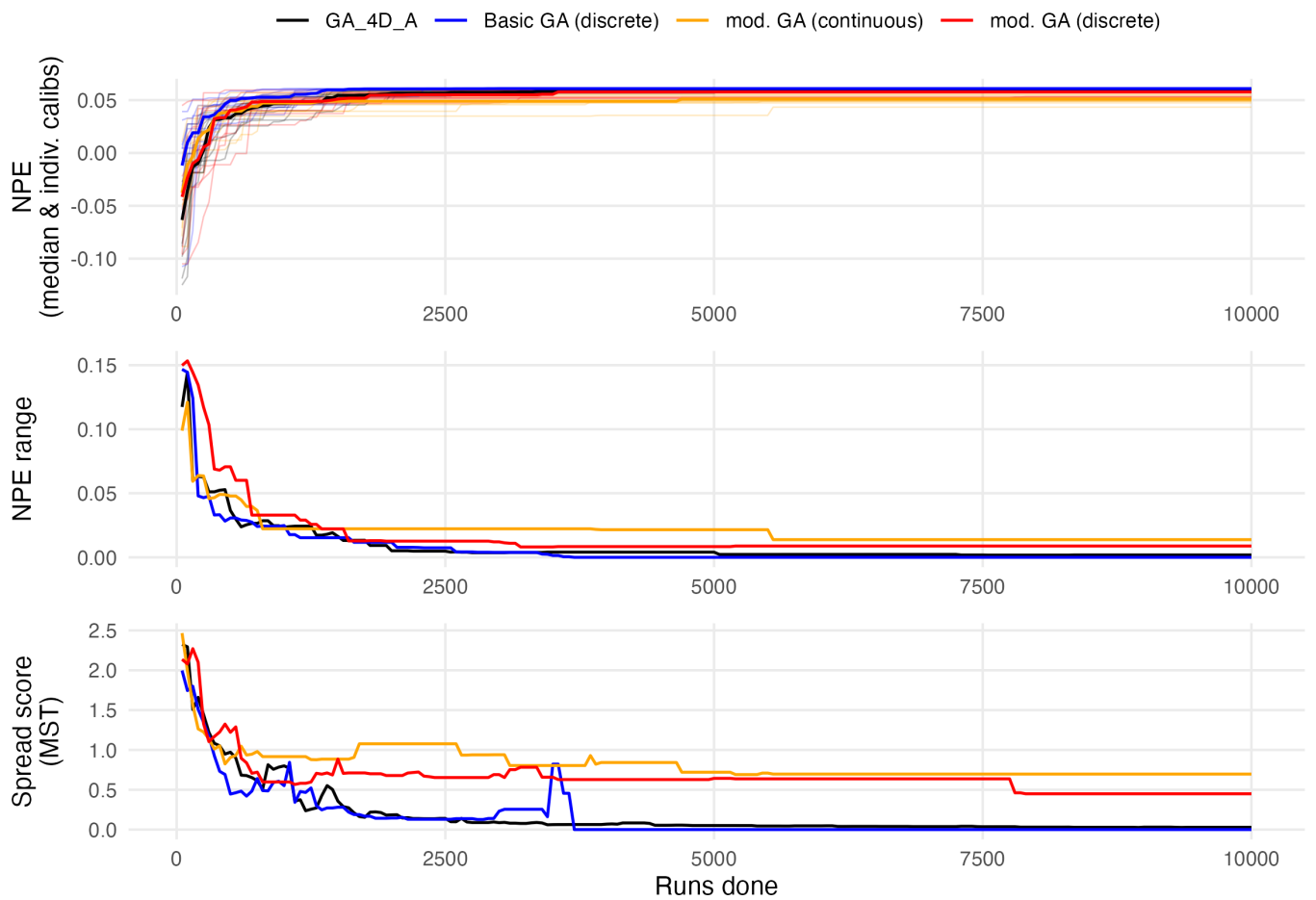
K1



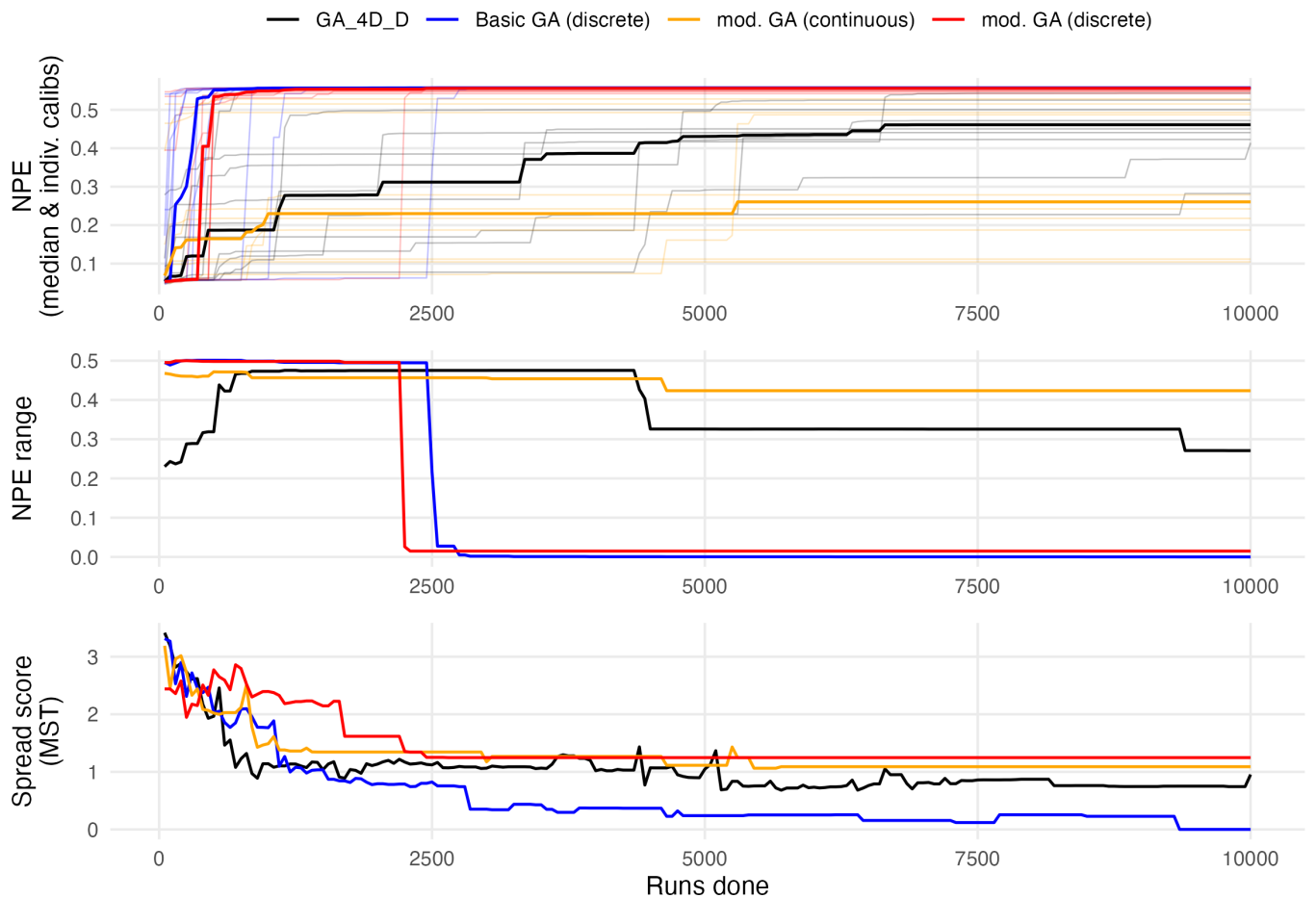
K2



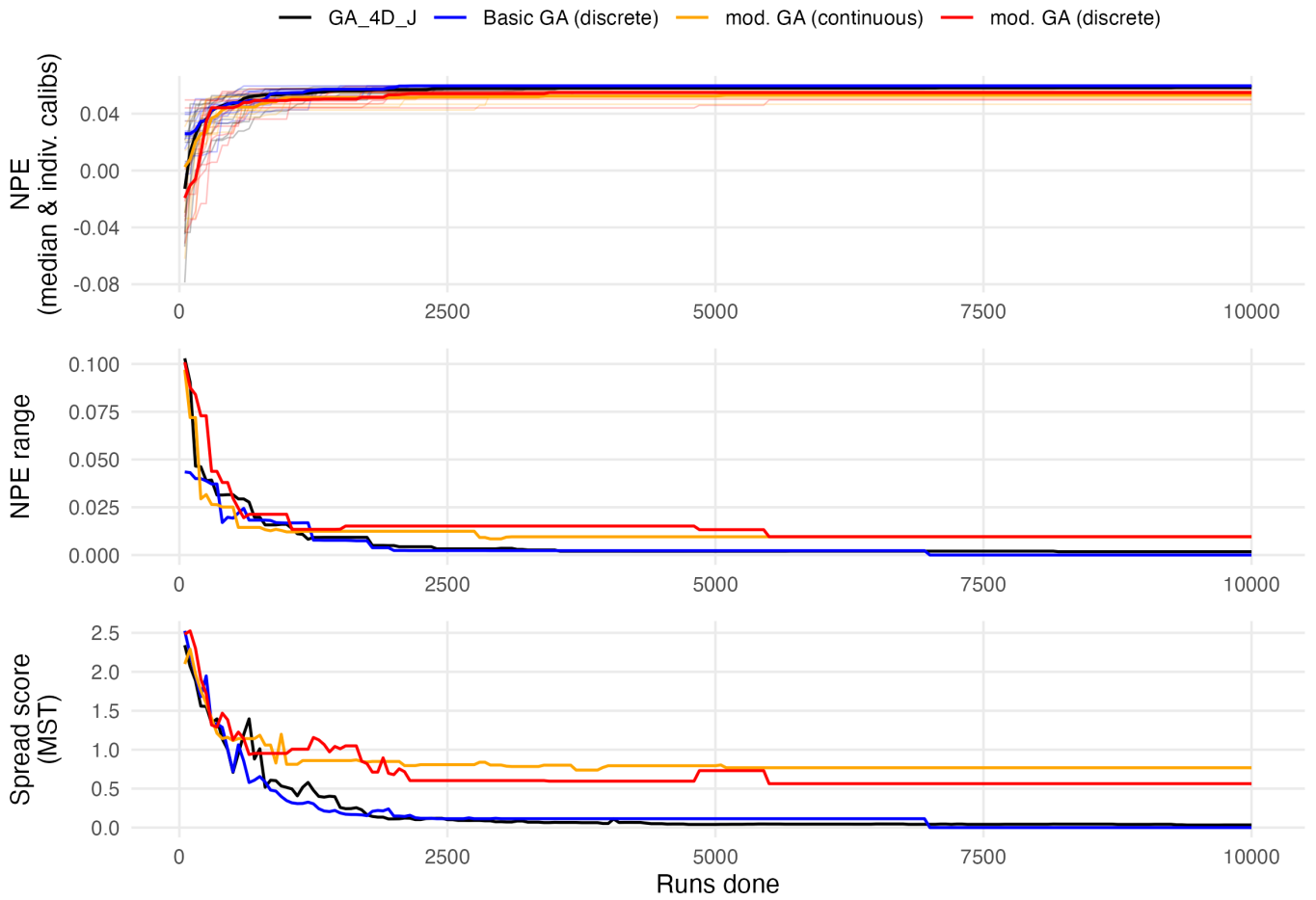
2155: GA_4D_A (10 GA Calibrations)



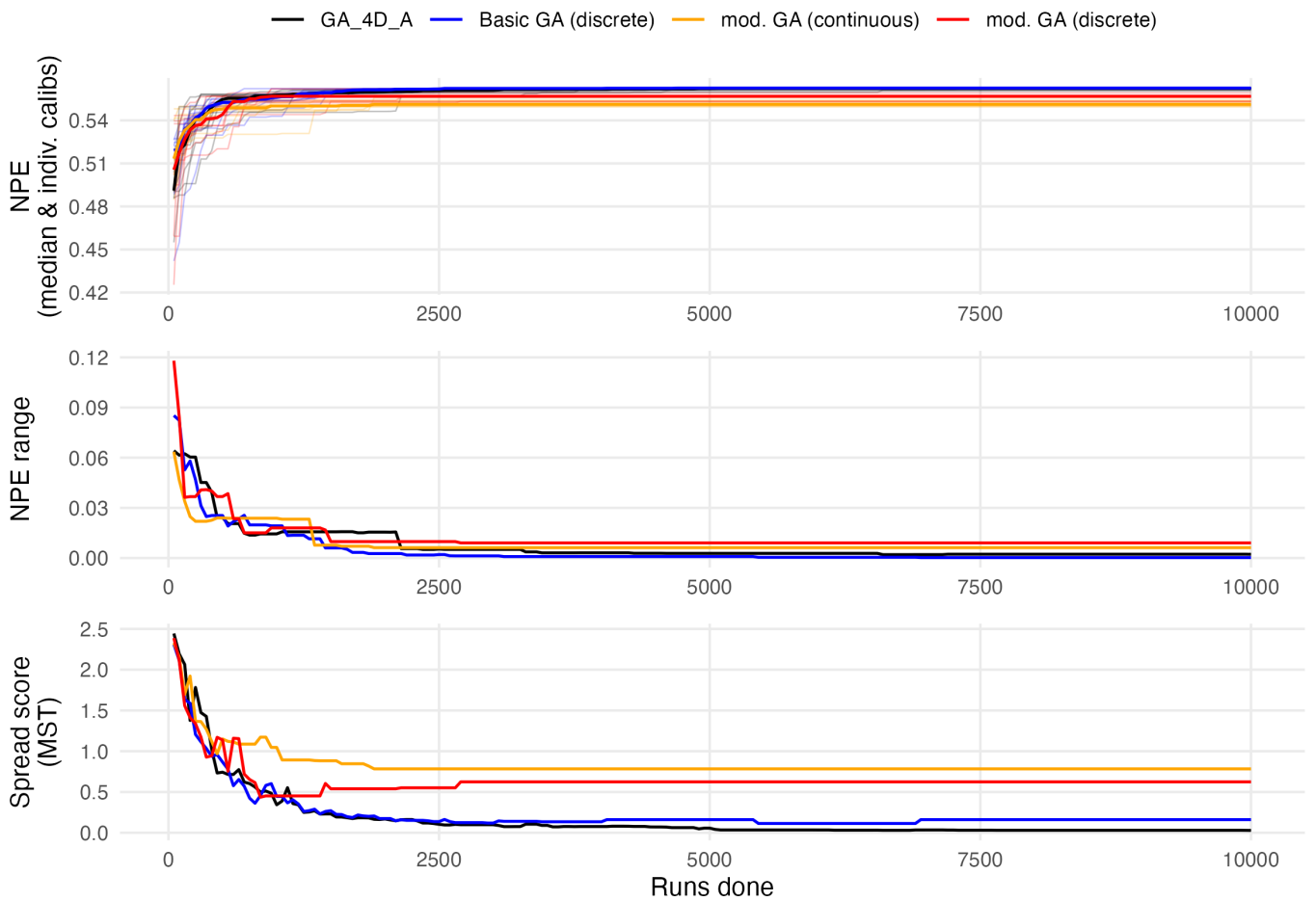
2155: GA_4D_D (10 GA Calibrations)



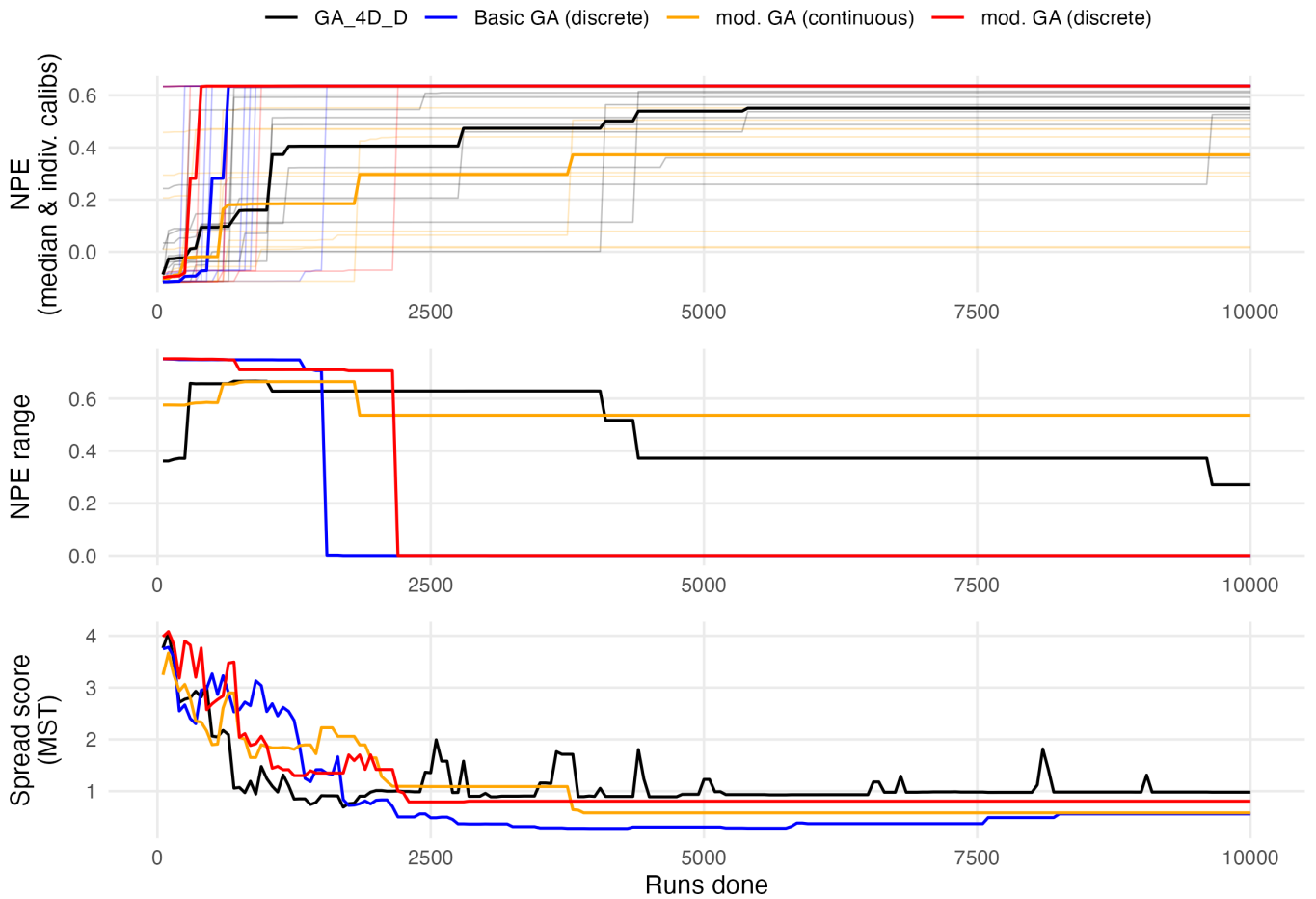
2155: GA_4D_J (10 GA Calibrations)



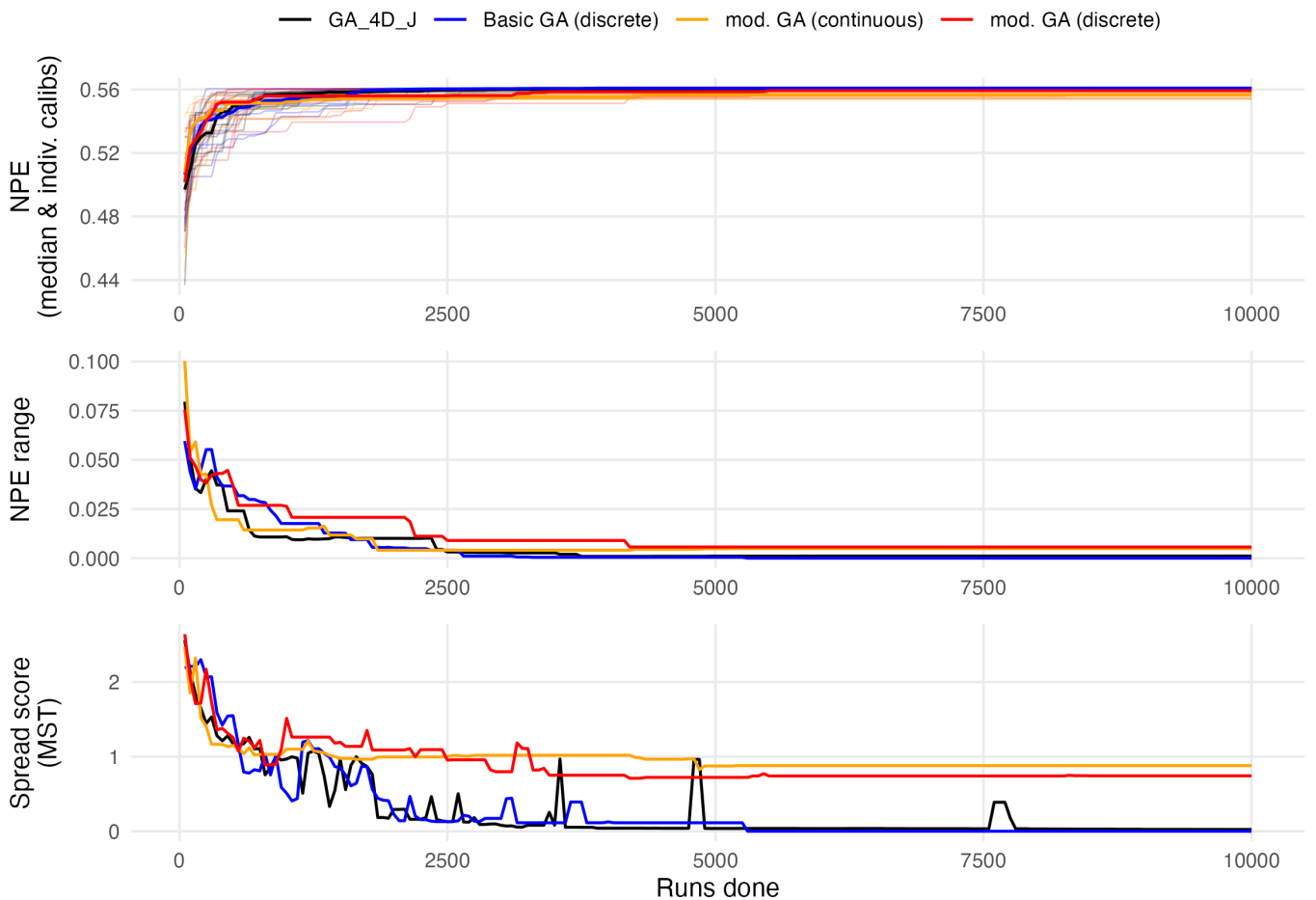
2403: GA_4D_A (10 GA Calibrations)



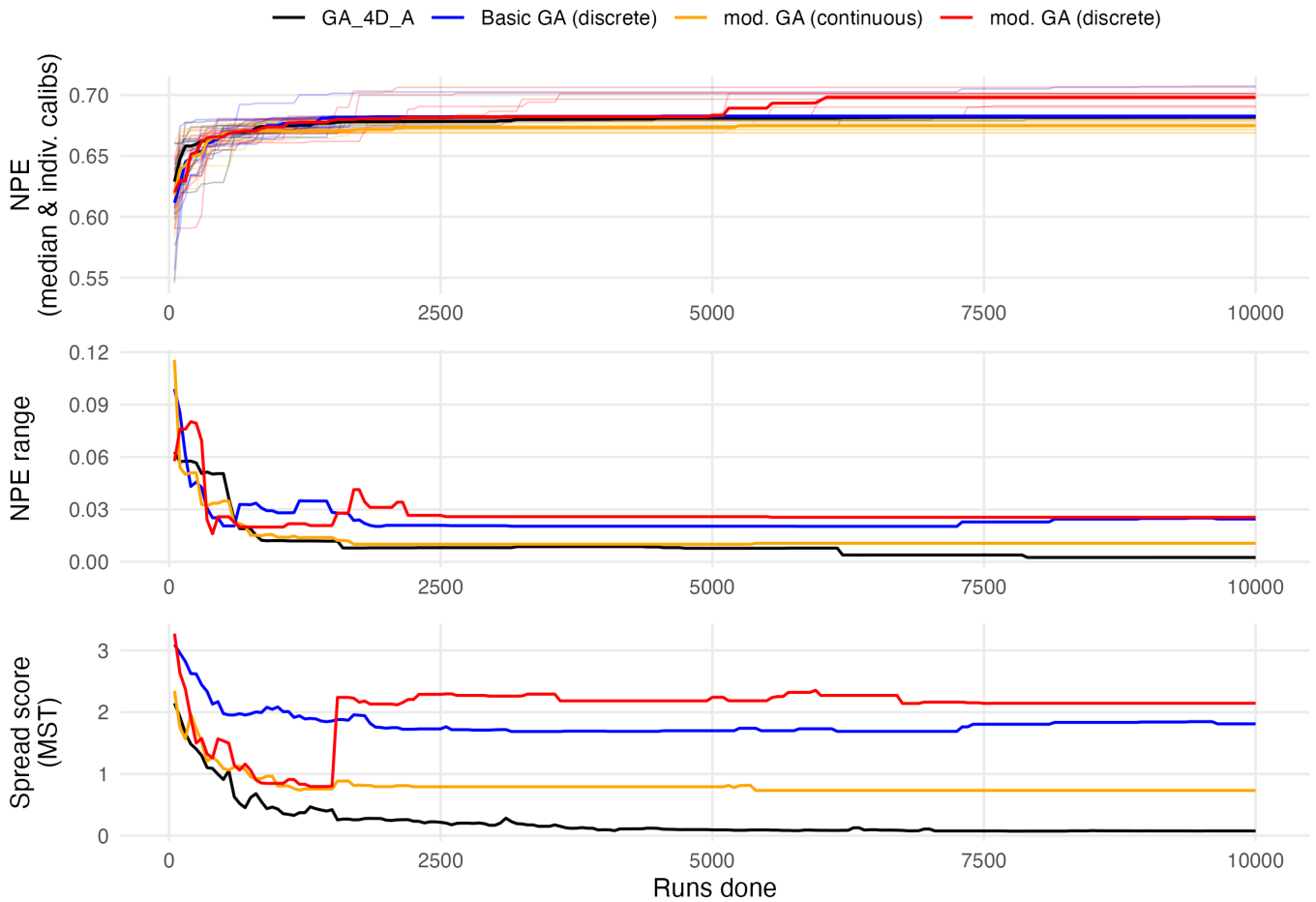
2403: GA_4D_D (10 GA Calibrations)



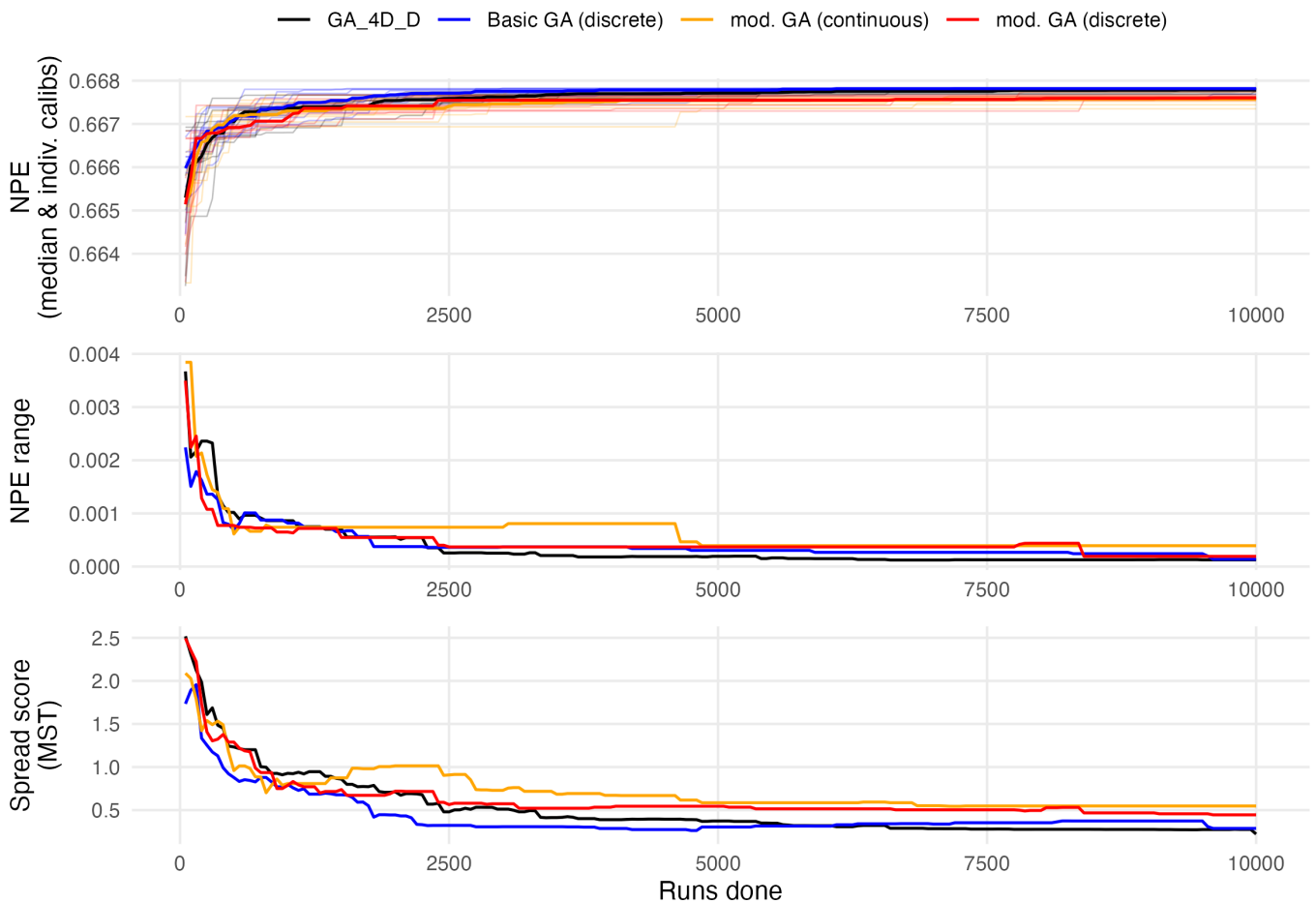
2403: GA_4D_J (10 GA Calibrations)



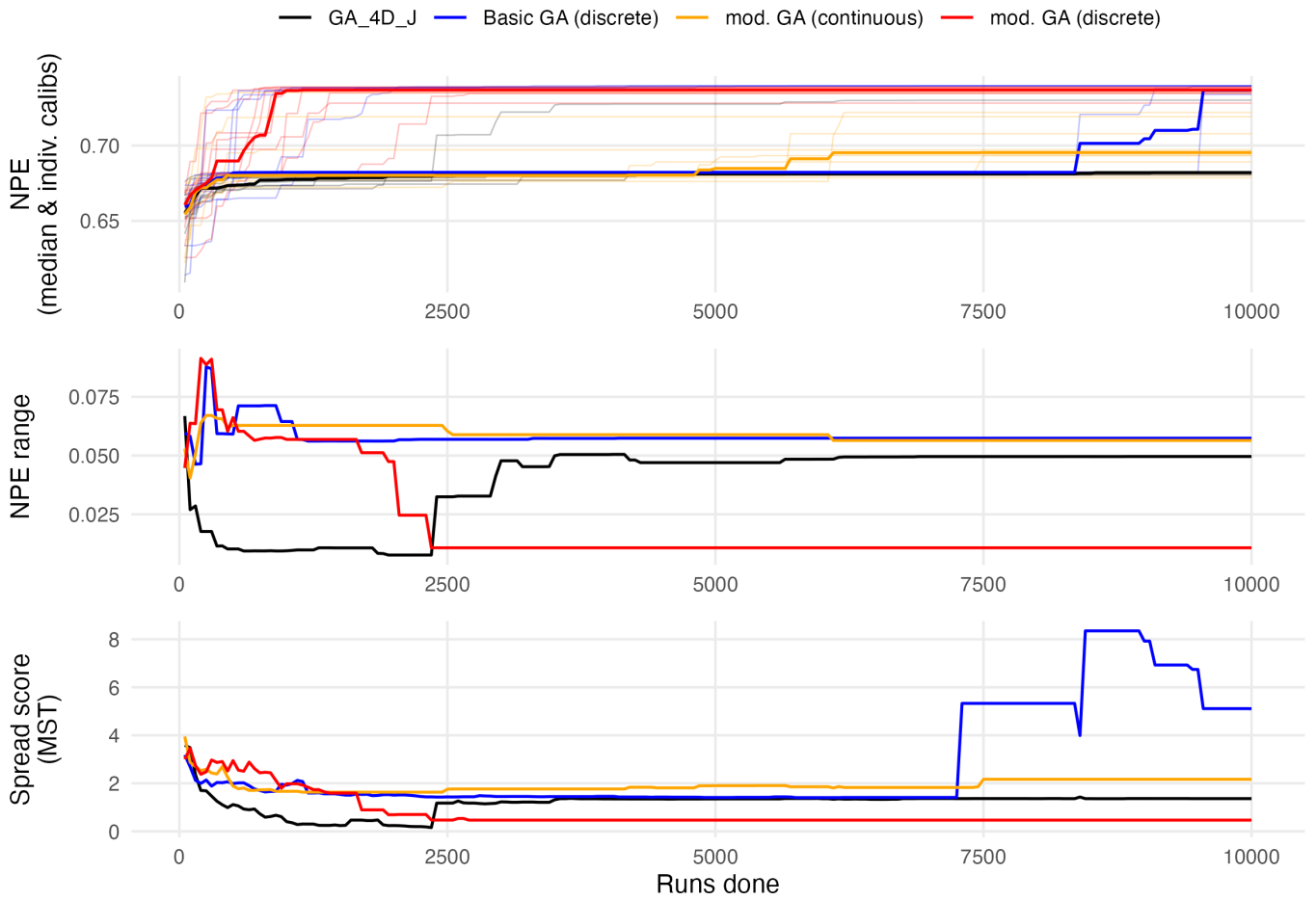
2426: GA_4D_A (10 GA Calibrations)



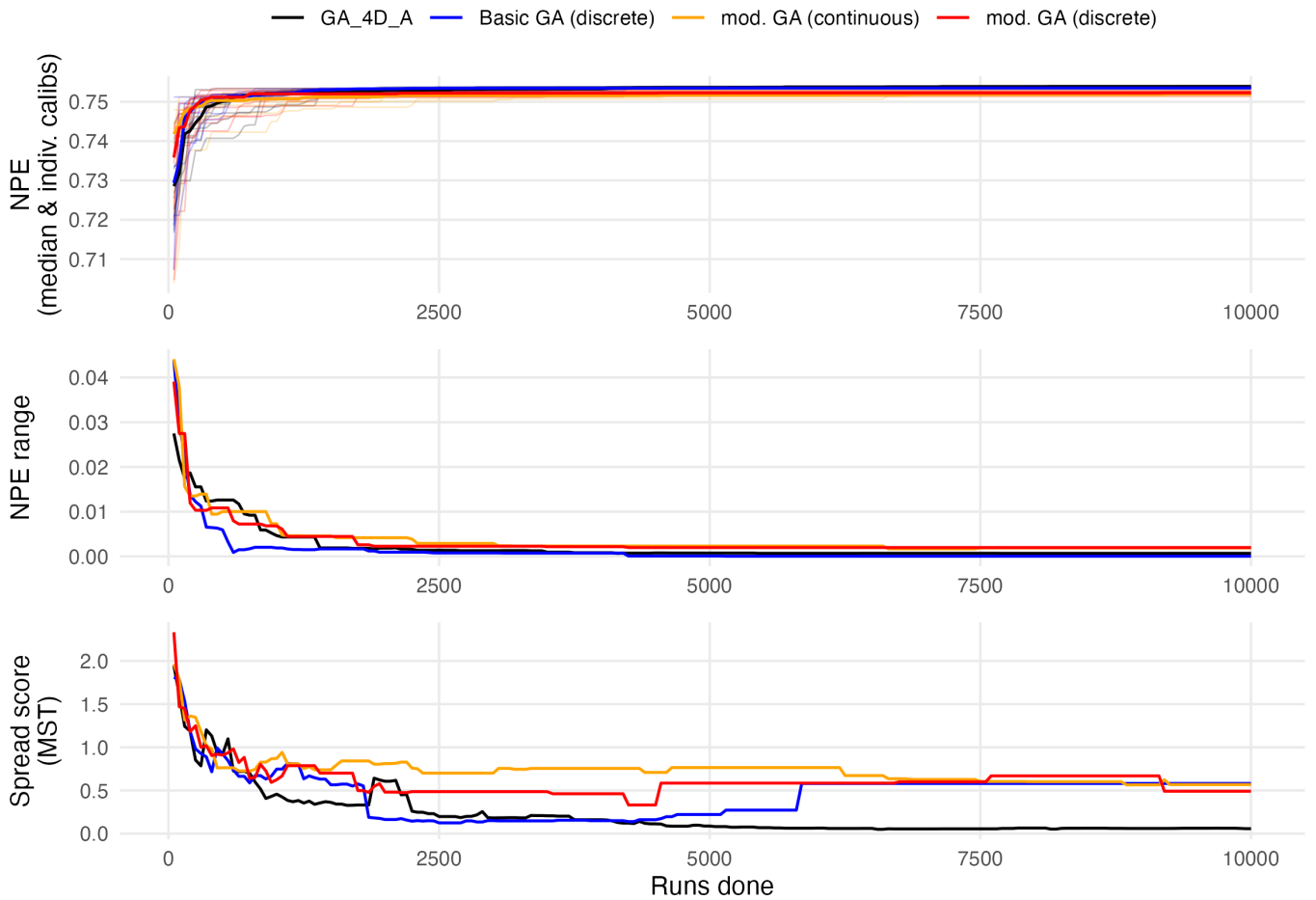
2426: GA_4D_D (10 GA Calibrations)



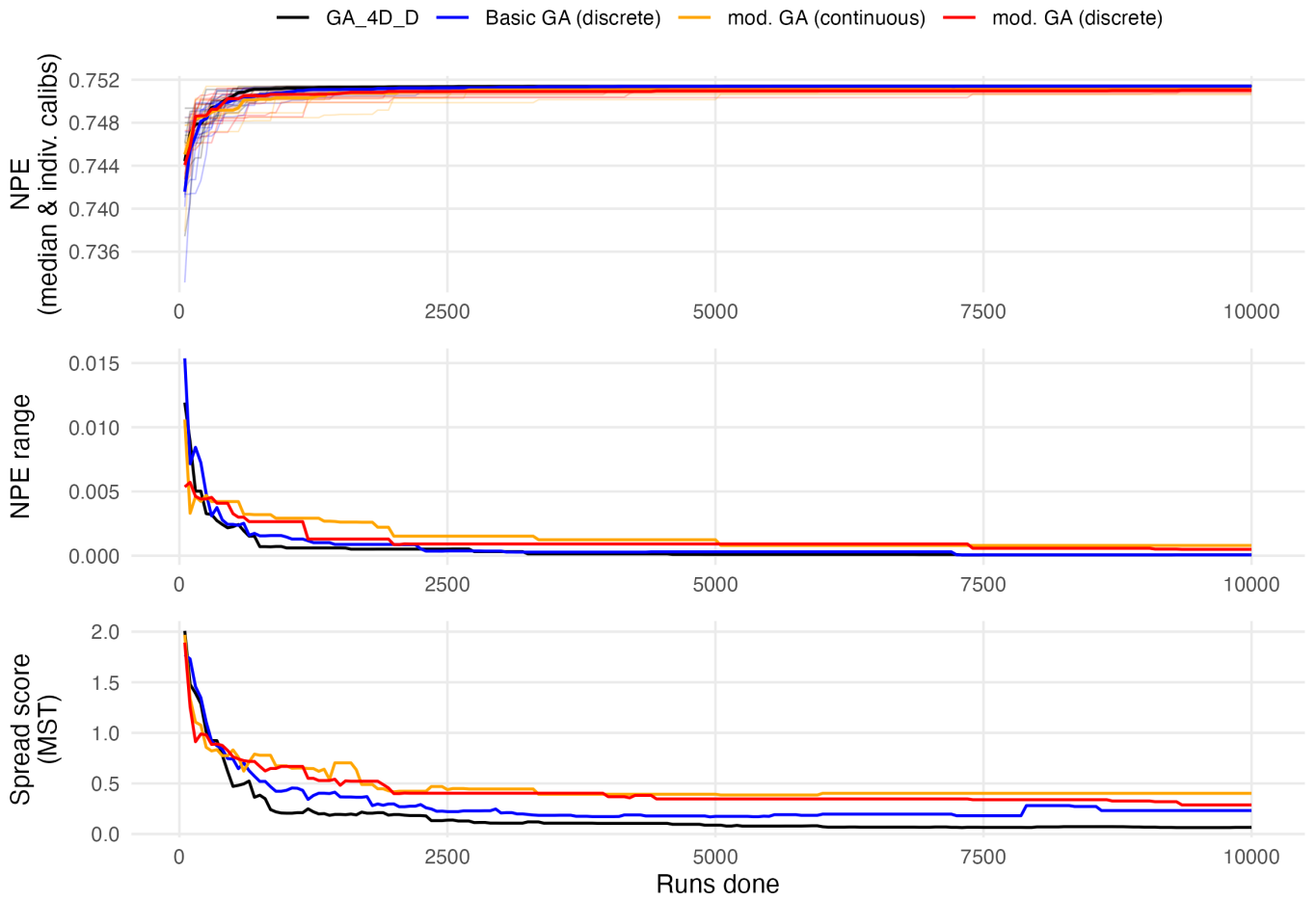
2426: GA_4D_J (10 GA Calibrations)



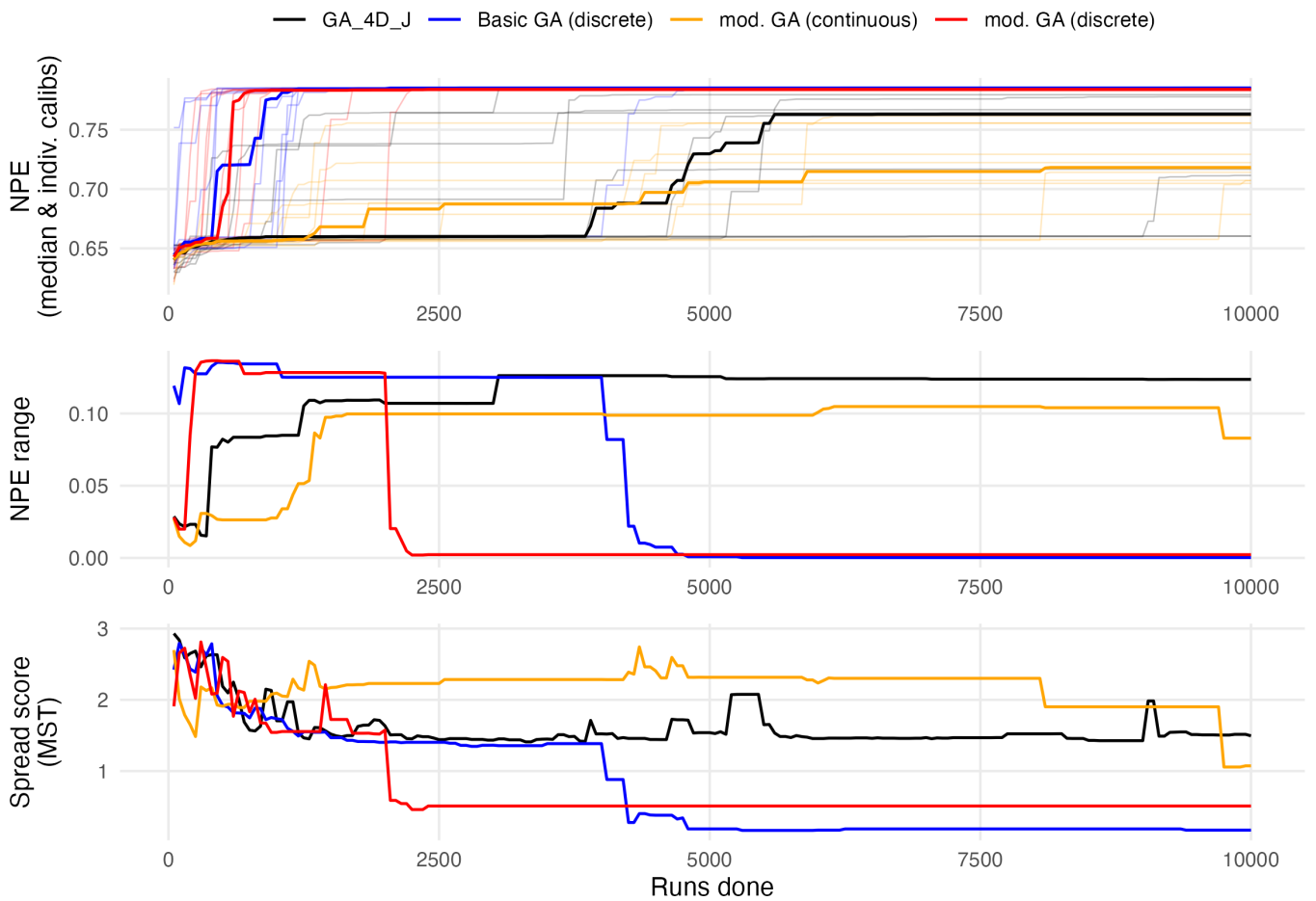
5014: GA_4D_A (10 GA Calibrations)



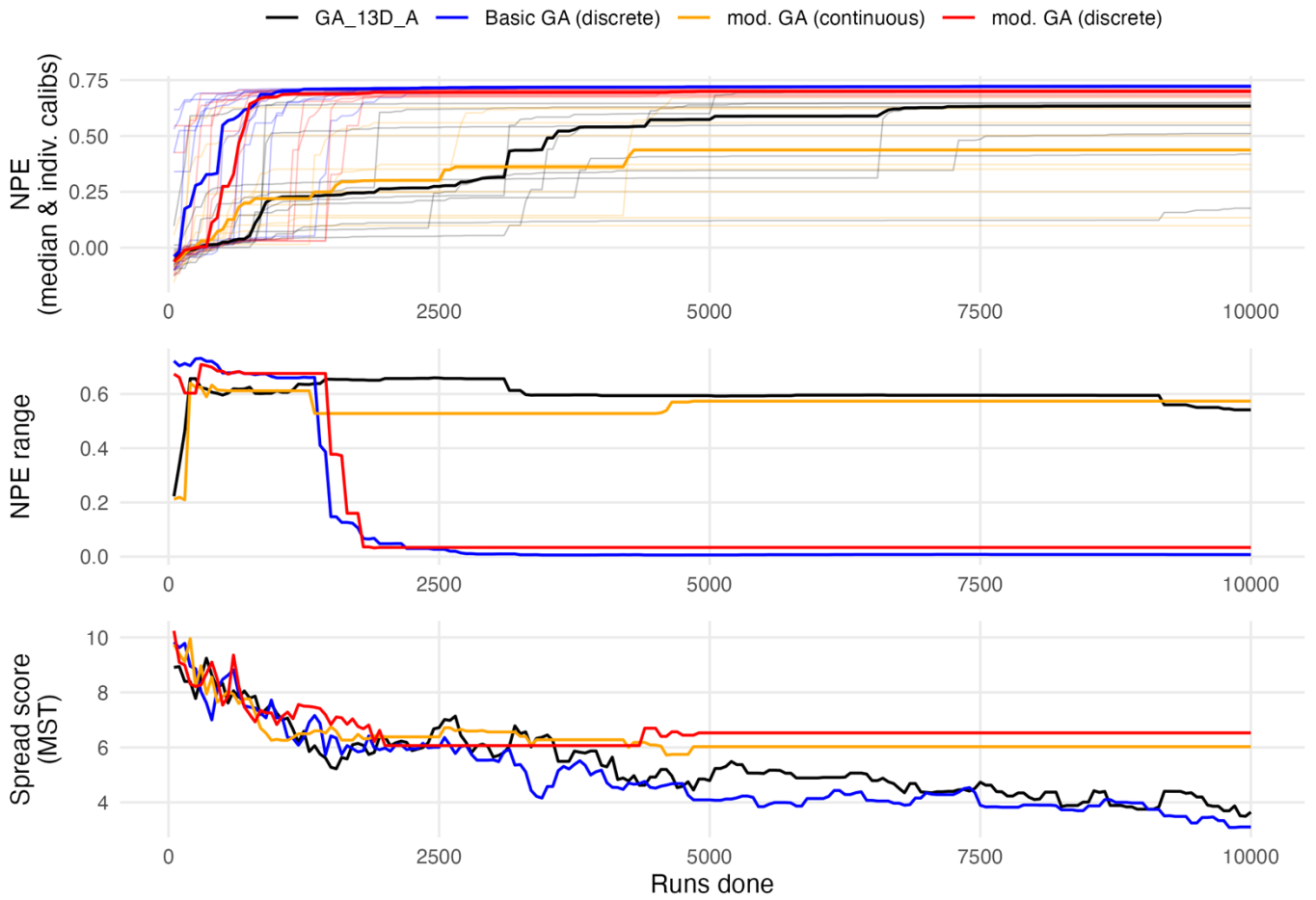
5014: GA_4D_D (10 GA Calibrations)



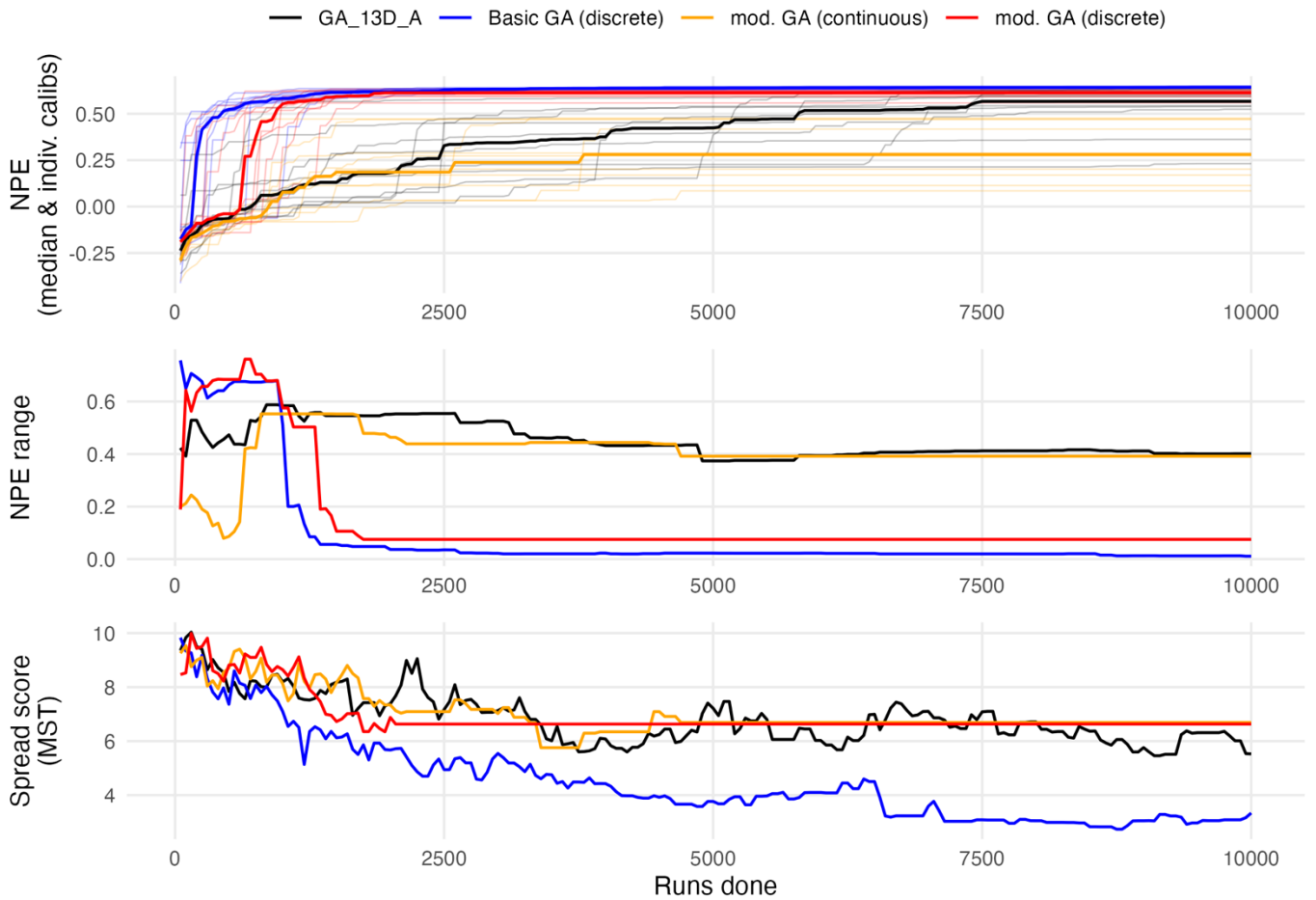
5014: GA_4D_J (10 GA Calibrations)



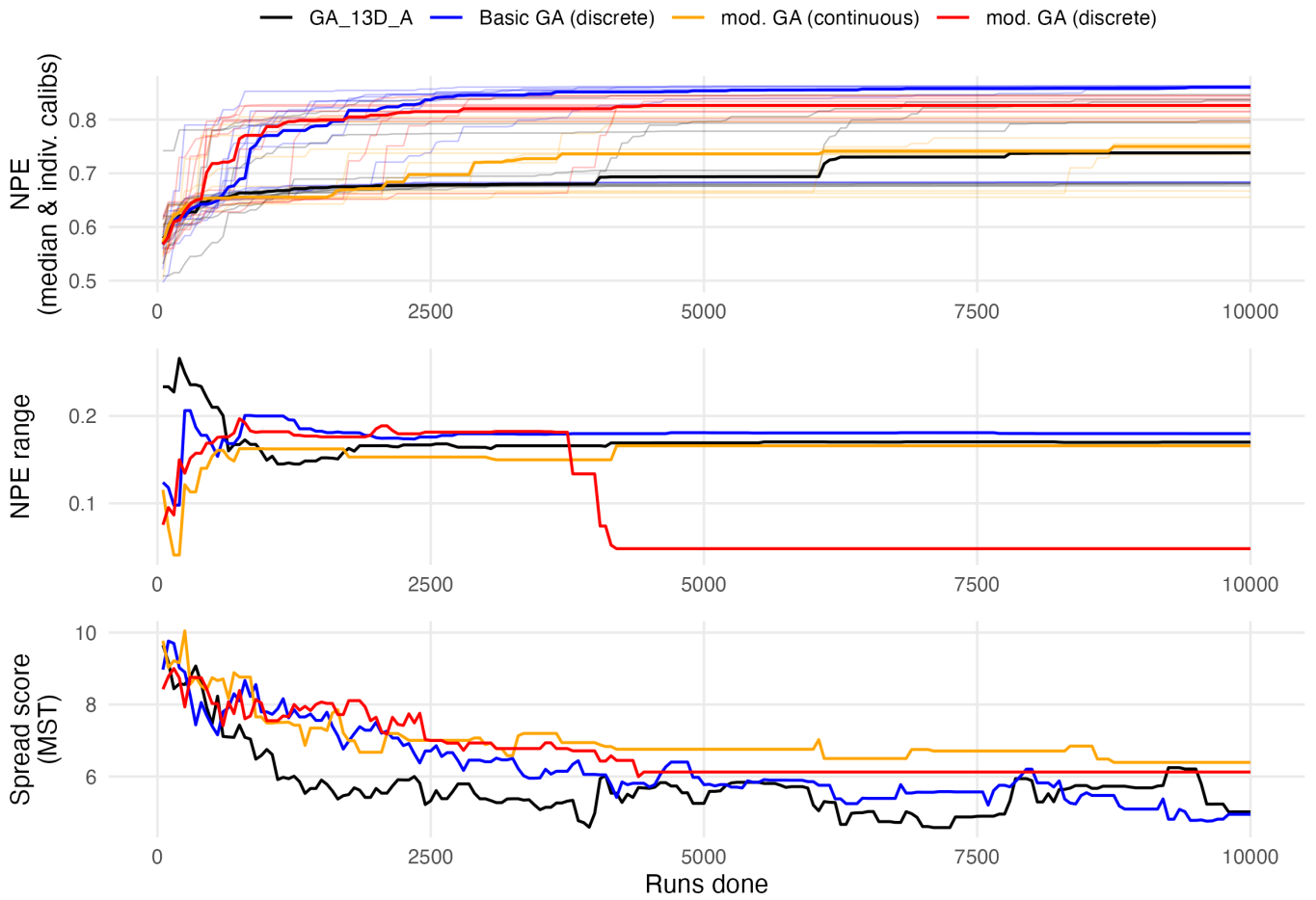
2155: GA_13D_A (10 GA Calibrations)



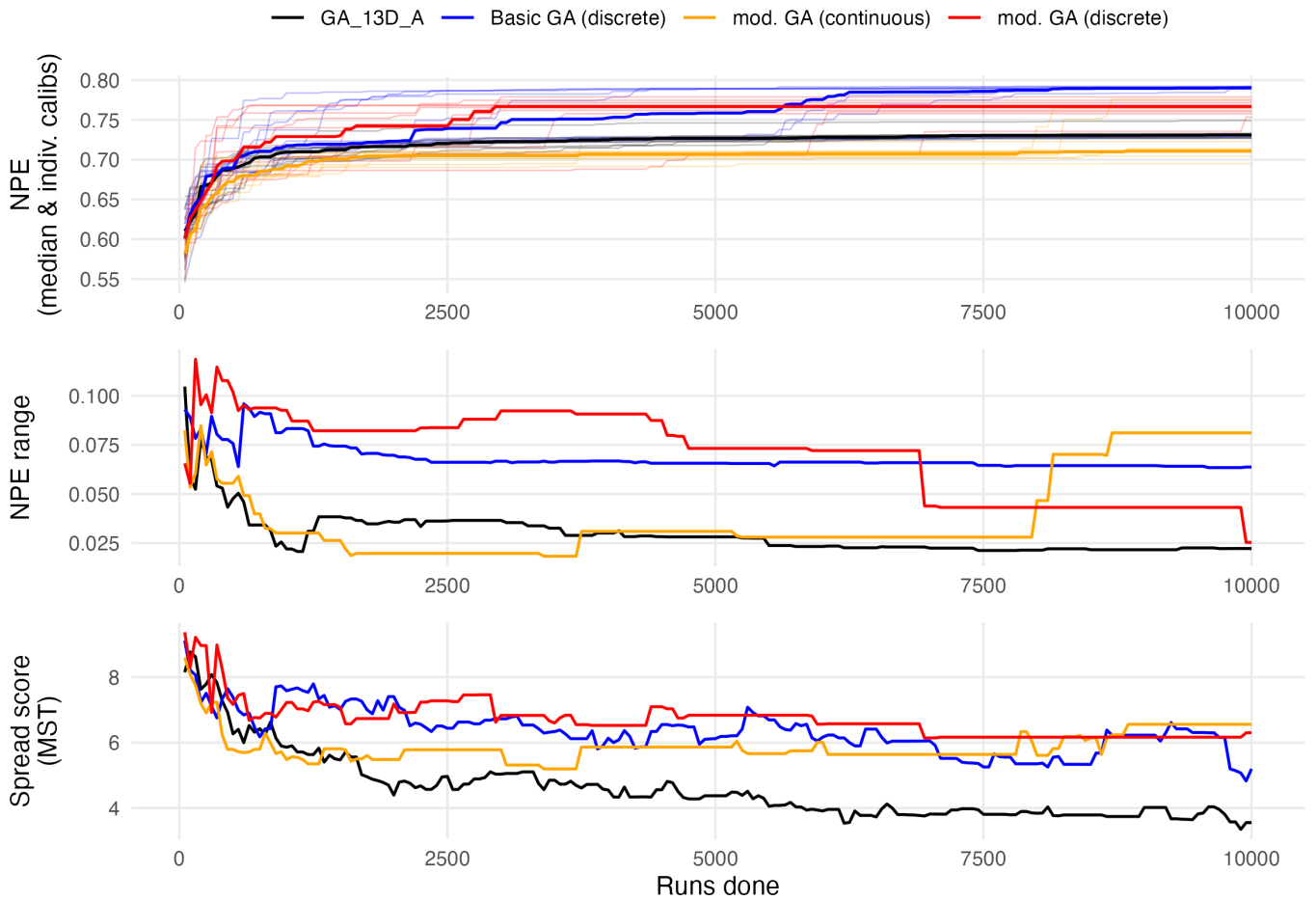
2403: GA_13D_A (10 GA Calibrations)



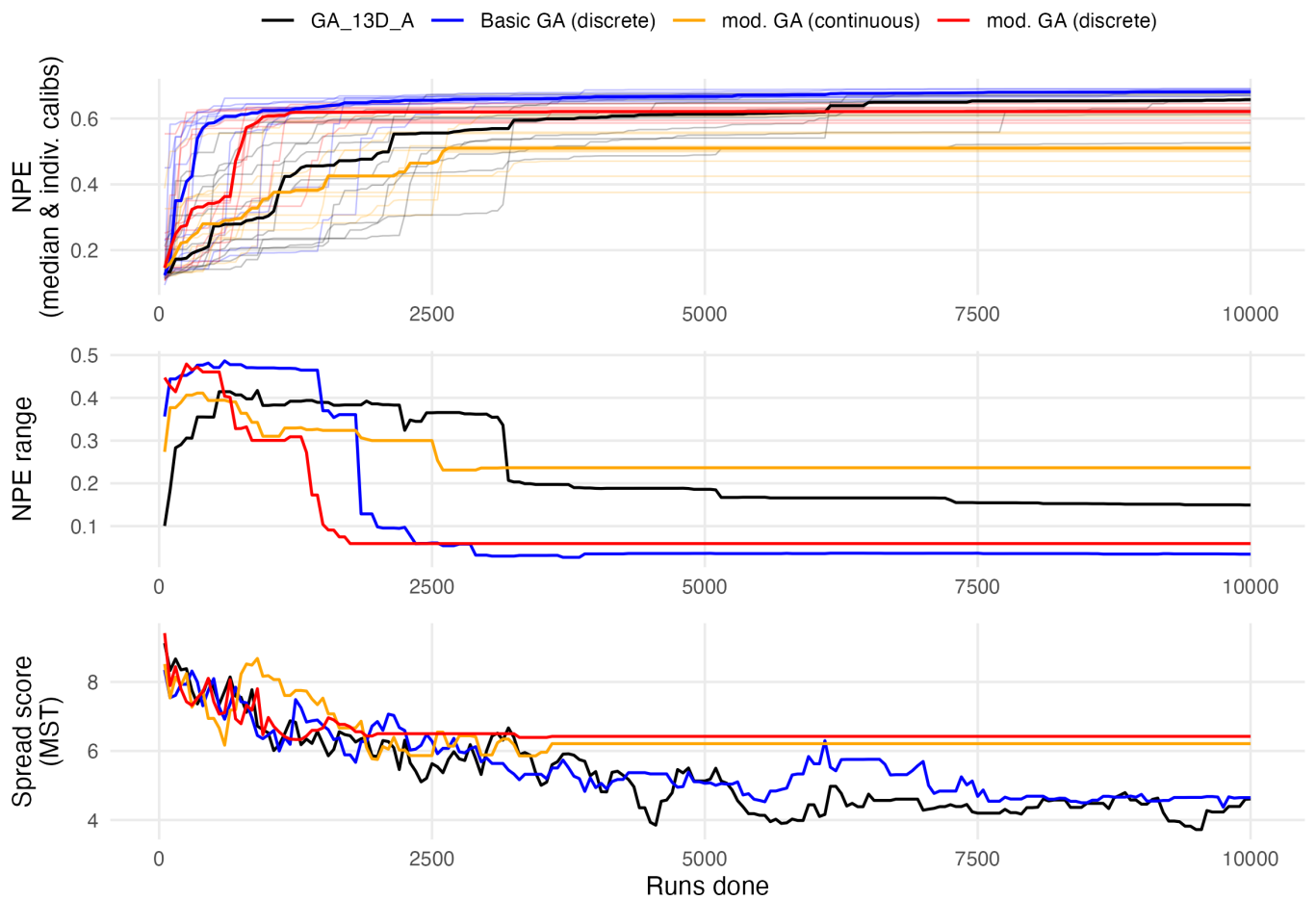
2426: GA_13D_A (10 GA Calibrations)



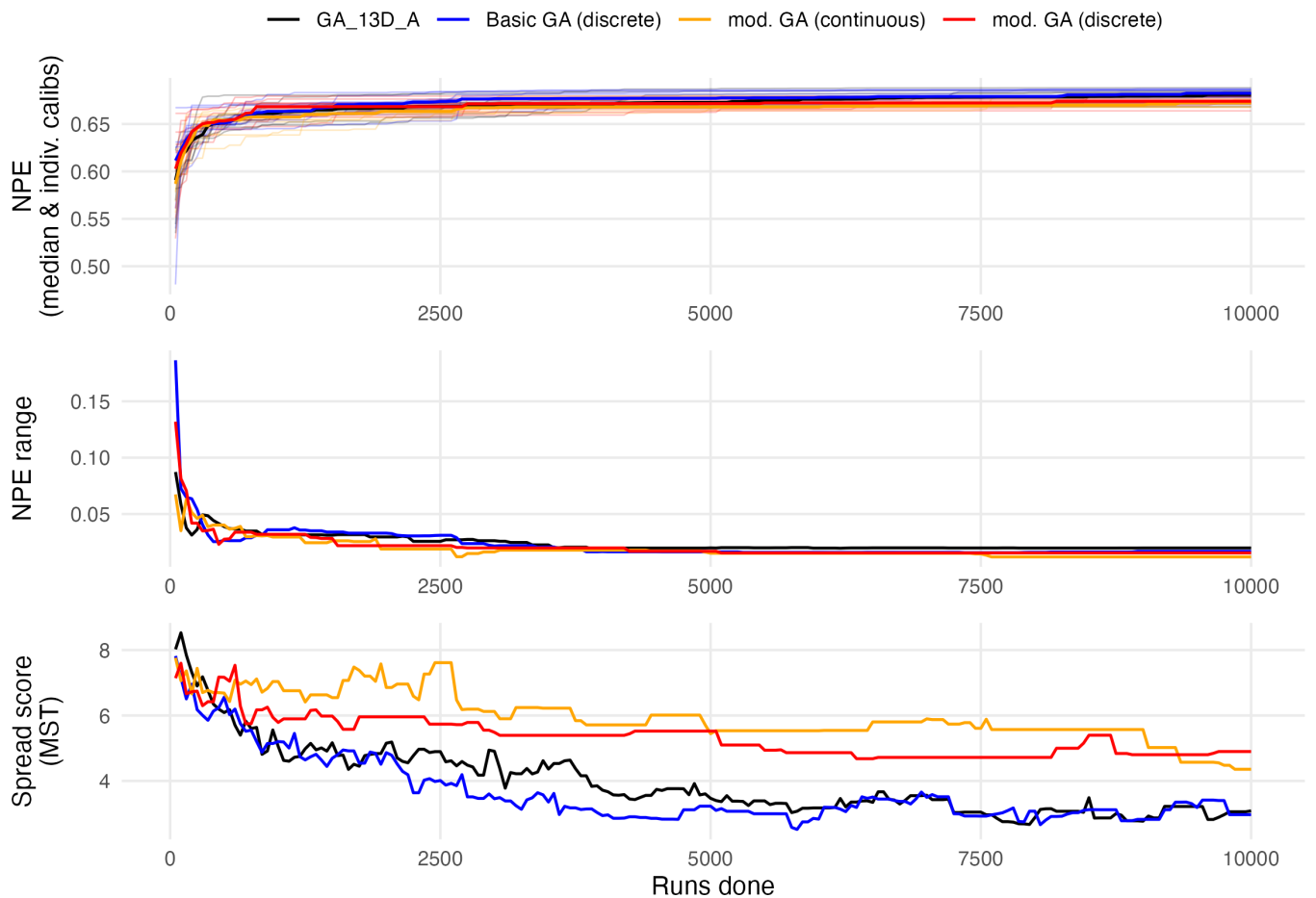
5014: GA_13D_A (10 GA Calibrations)



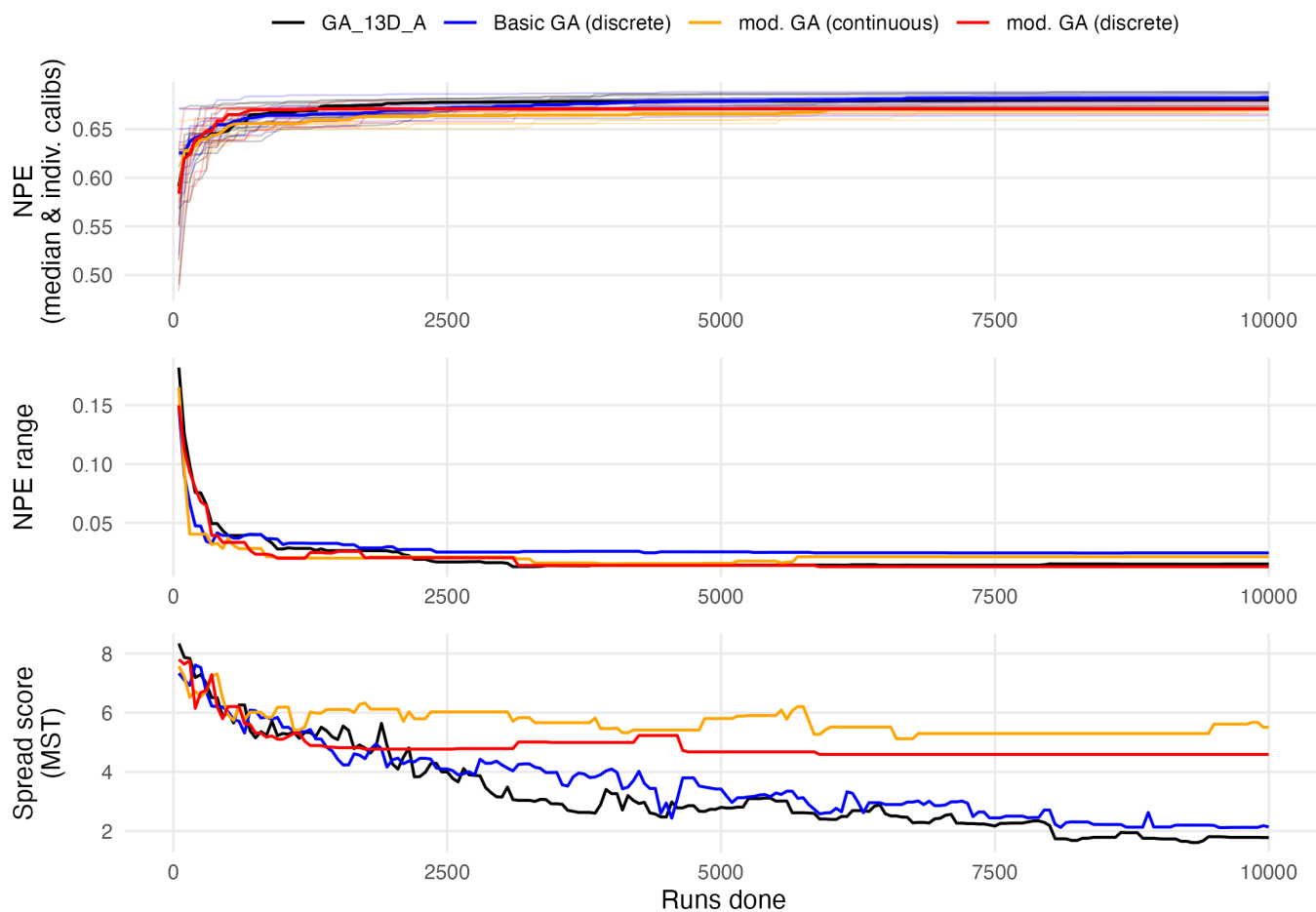
CZ000098: GA_13D_A (10 GA Calibrations)



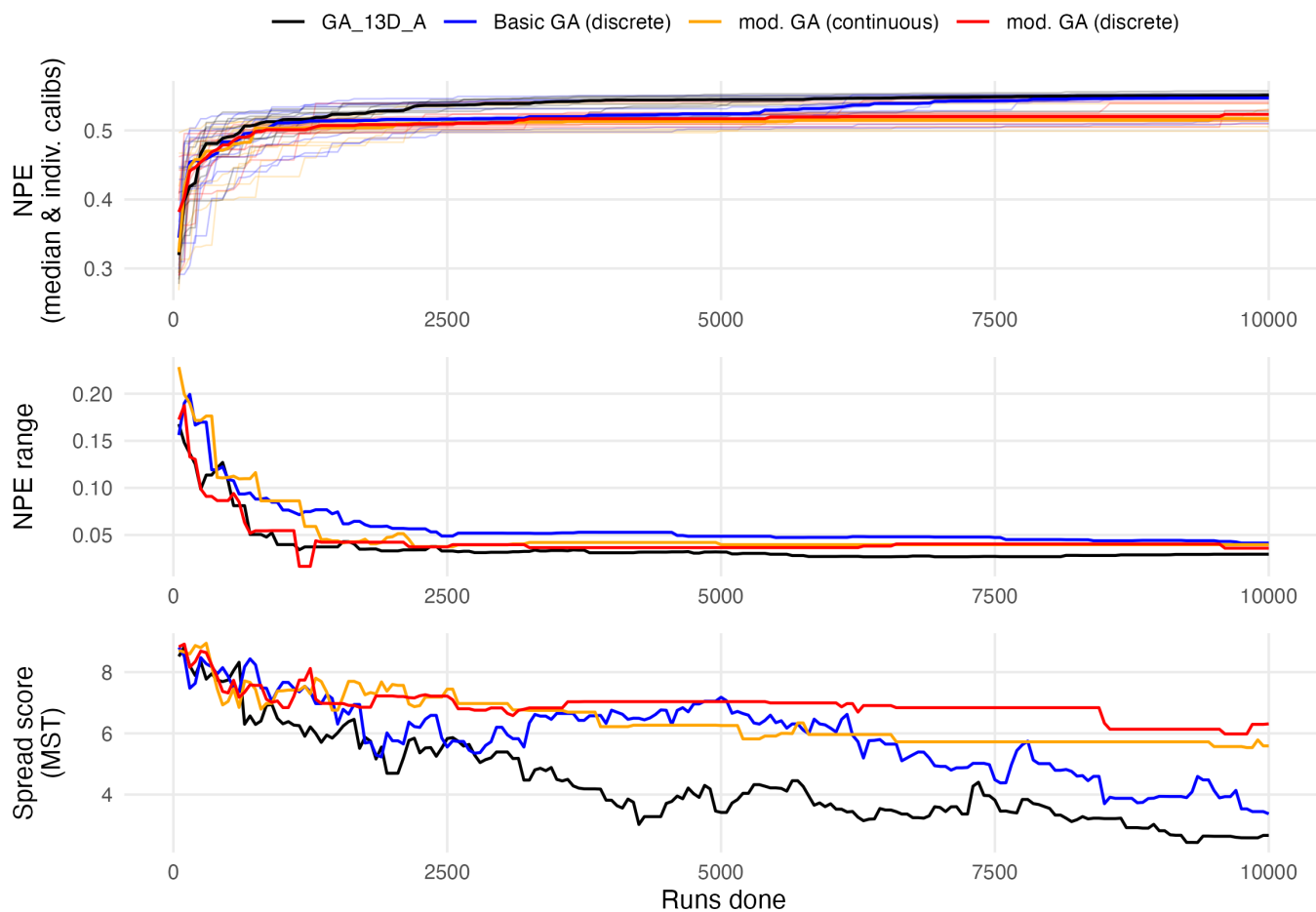
DEBB0132: GA_13D_A (10 GA Calibrations)



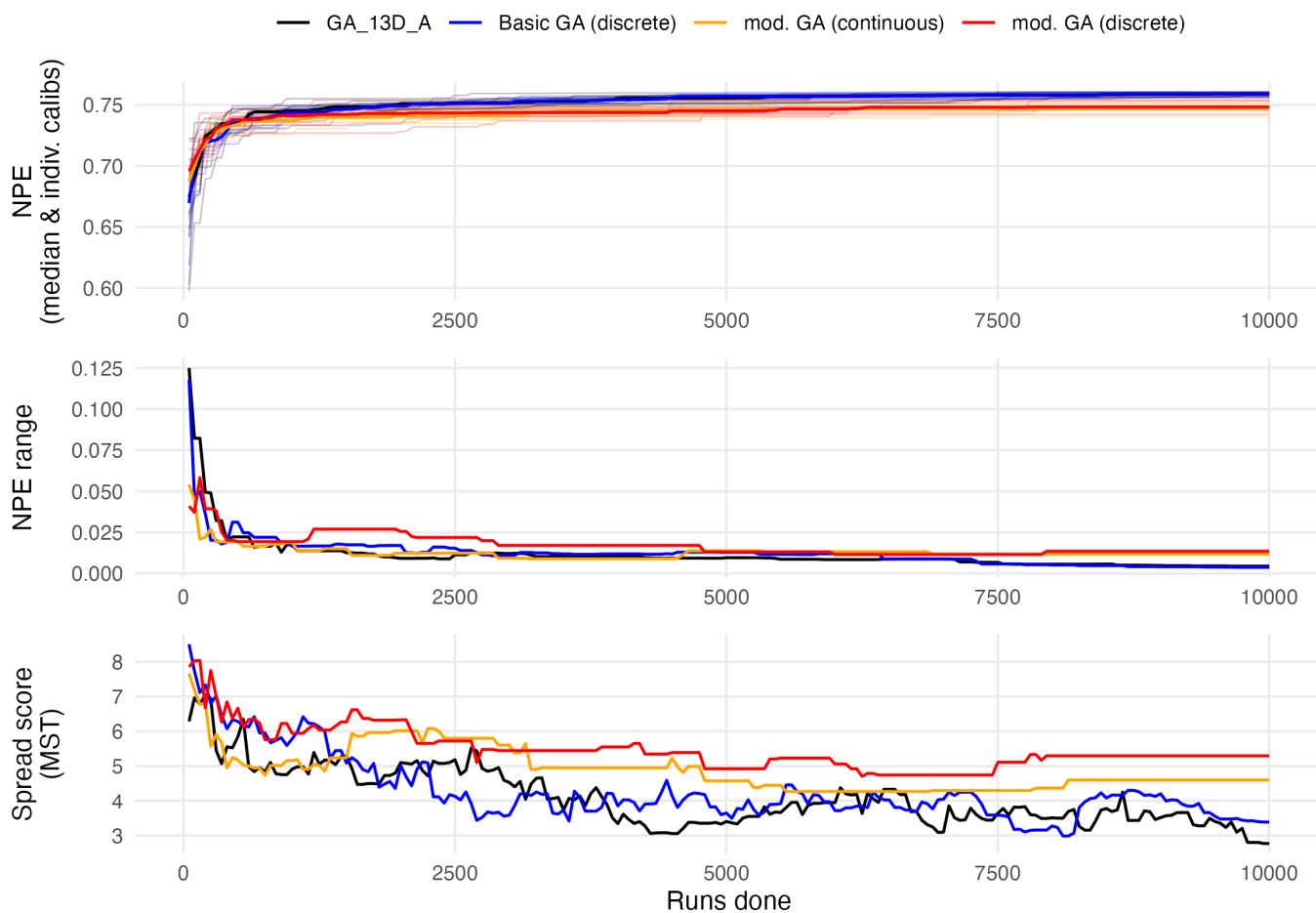
DEBB0136: GA_13D_A (10 GA Calibrations)



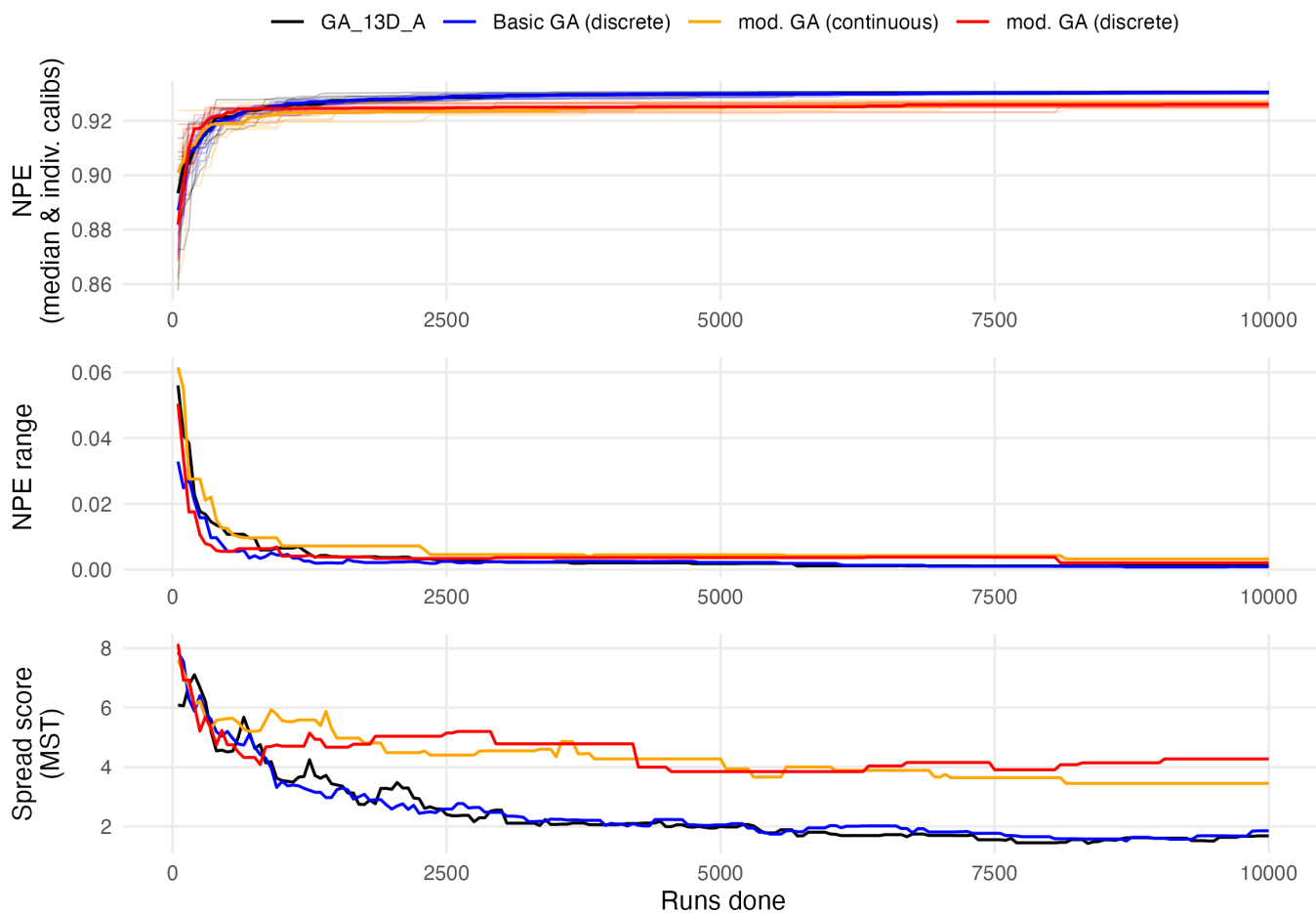
ES000356: GA_13D_A (10 GA Calibrations)



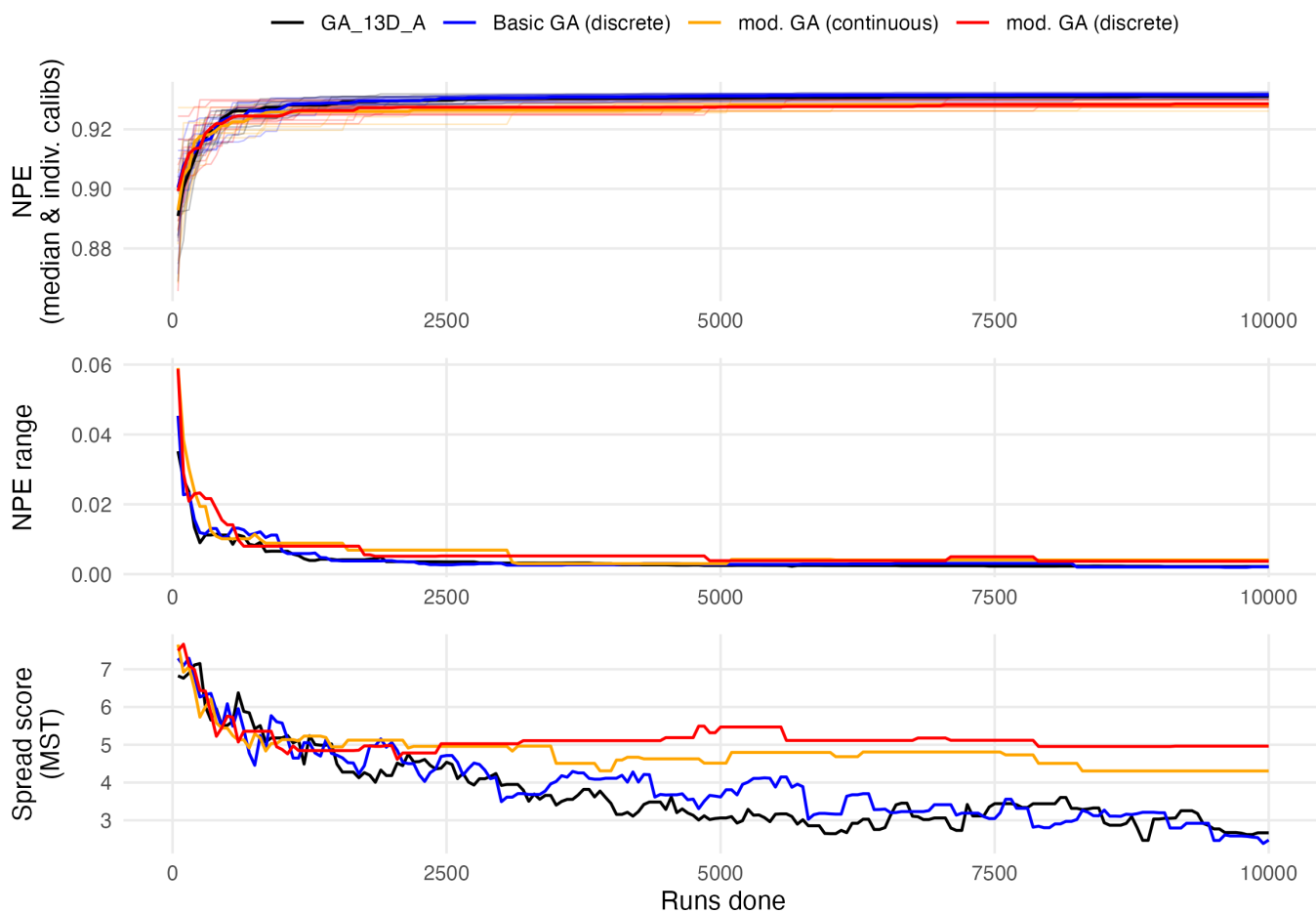
ES001323: GA_13D_A (10 GA Calibrations)



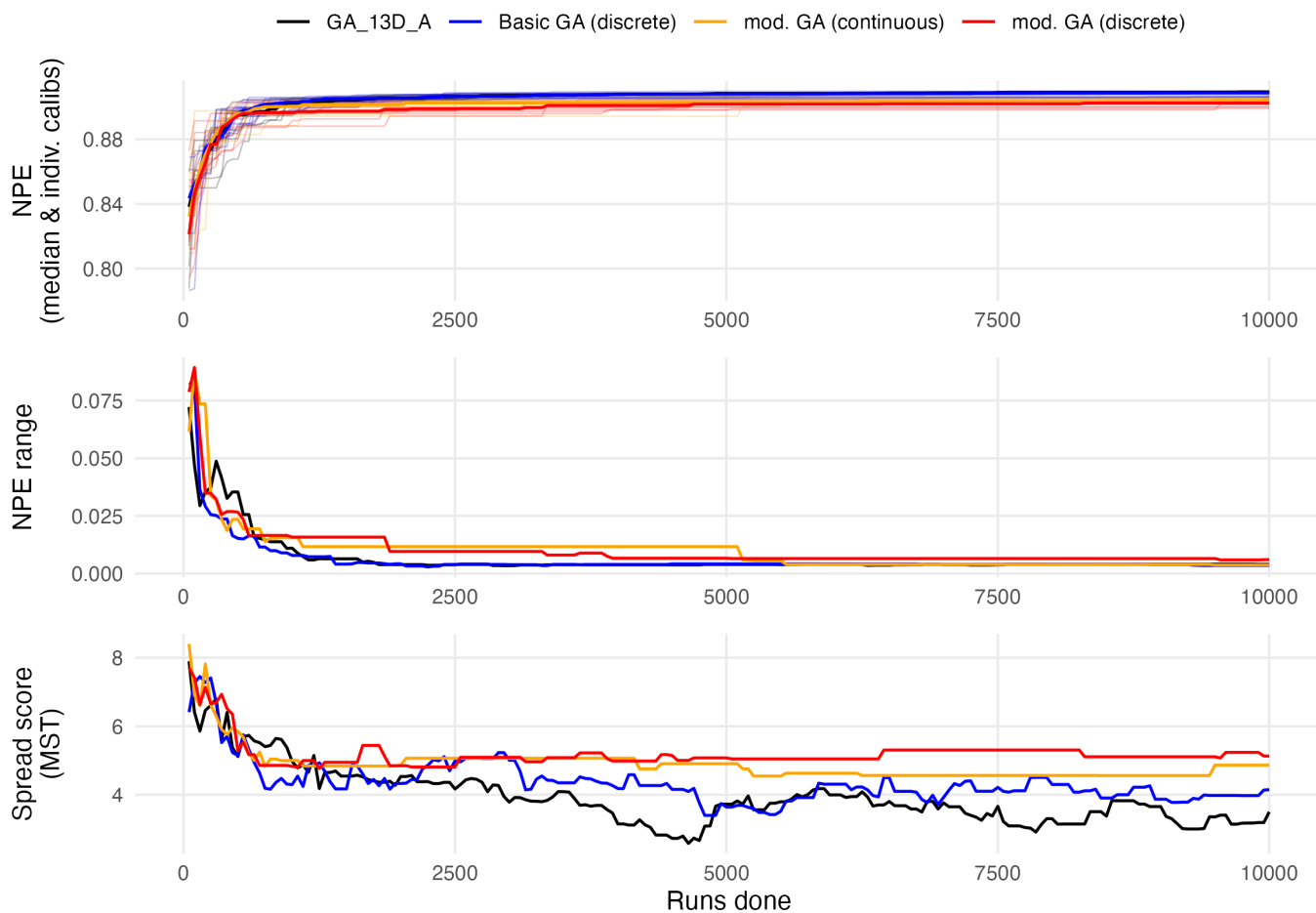
FR000672: GA_13D_A (10 GA Calibrations)



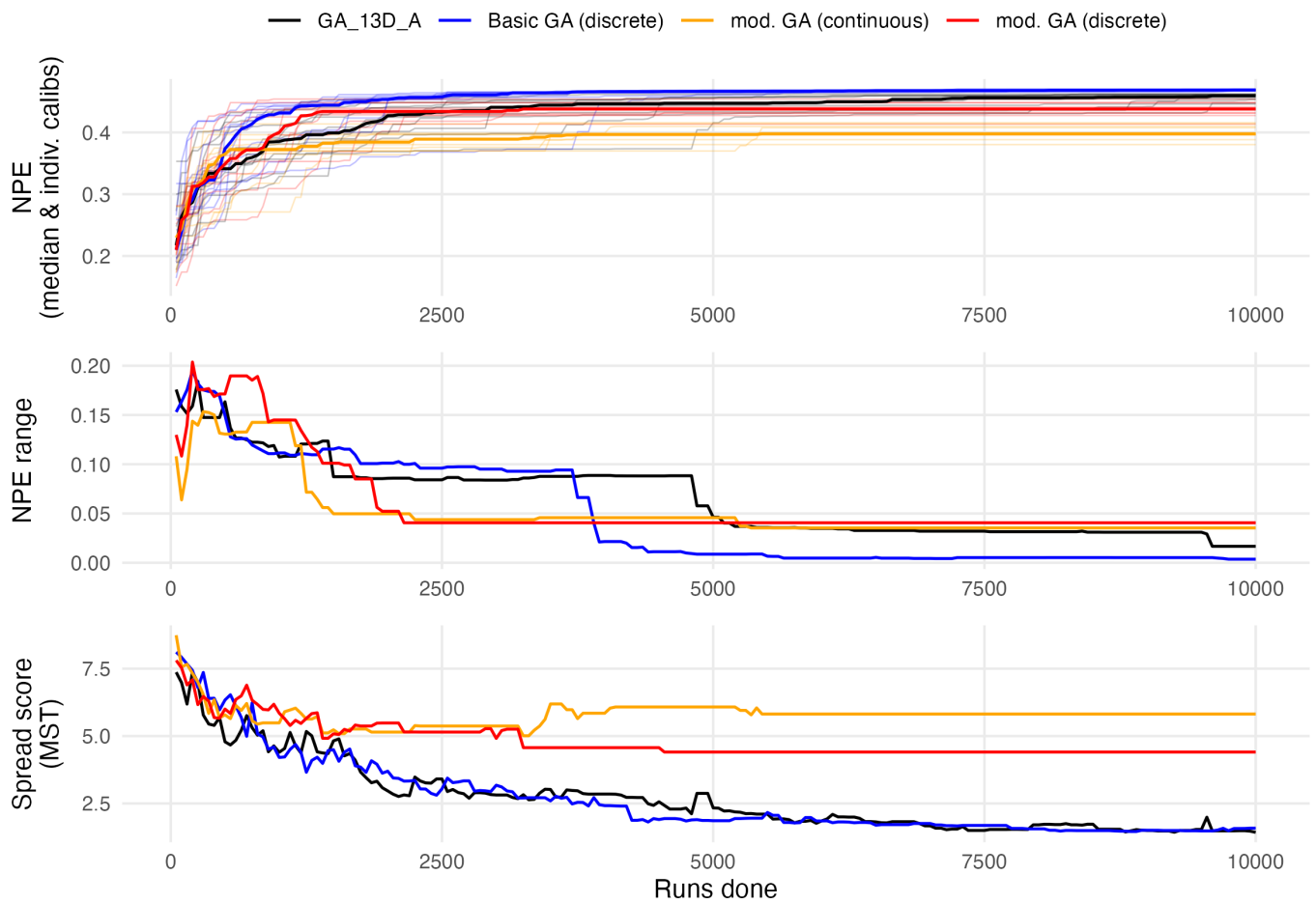
FR000730: GA_13D_A (10 GA Calibrations)



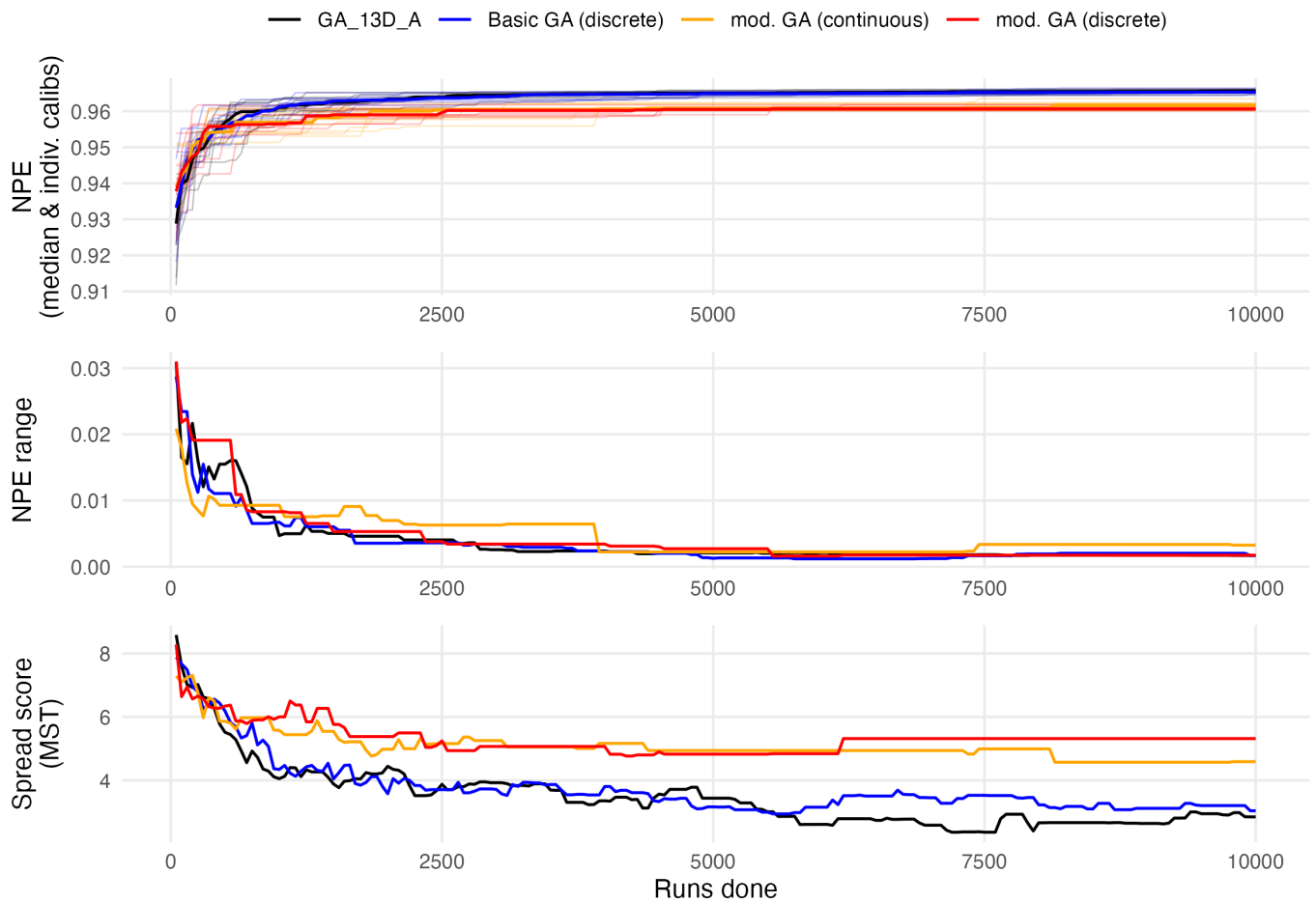
FR001413: GA_13D_A (10 GA Calibrations)



GB000296: GA_13D_A (10 GA Calibrations)



GB000494: GA_13D_A (10 GA Calibrations)



Declaration of Independence

Personal declaration: I hereby declare that this thesis is the result of my own independent work. All external sources and contributions have been explicitly acknowledged.

Basel, April 2026

A handwritten signature in black ink, appearing to read 'L. Andrey', with a stylized, flowing script.

Lionel Andrey