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Dakota-SAS4A/SASSYS-1 Coupling for Uncertainty Quantification and Optimization Analysis

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Abstract - *Argonne has been leading the safety analysis of Sodium-cooled Fast Reactors under protected and unprotected transient events by developing and maintaining the system code SAS4A/SASSYS-1. In these analyses, some assumptions must be made for the models because of the uncertainties related to the heat transfer systems; the propagation of nuclear data uncertainties also has significant impact on the reactivity coefficients. In order to estimate the safety related parameters (e.g. coolant boiling margin, peak fuel temperature) more accurately, SAS4A/SASSYS-1 has recently been coupled with uncertainty quantification toolkits, including Dakota and RAVEN. The objectives of this paper are to present the coupling and demonstrate the capabilities of the uncertainty quantification and design optimization. The unprotected transients of Argonne's Advanced Burner Test Reactor (ABTR) were examined in this study. A sensitivity analysis was conducted within the uncertainty domain considering five uncertain parameters. It was found that core radial expansion has the most significant impact on the safety performance because of the large negative feedback during the Unprotected Loss of Heat Sink (ULOHS). The uncertainty quantification of the minimum boiling margin and the peak fuel temperature is discussed in response to the uncertainty propagation. Beyond the conventional sampling techniques, two additional advanced sampling techniques (i.e. Importance Sampling and Reliability Method) were tested. Another objective of the coupling is to optimize the design for the potential to improve the safety performance. The peak fuel temperature during the ABTR ULOHS is minimized by perturbing the Doppler feedback coefficient and radial expansion feedback coefficient. Three optimizers supported by Dakota have been tested and finally a hybrid method is recommended for the SAS4A/SASSYS-1 system optimization in the future due to its efficiency for the global optimum.*

I. INTRODUCTION

Advancements in the knowledge of nuclear reactor performance have led to an increased need to perform Uncertainty Quantification (UQ) in the advanced reactor domain. The role of uncertainty quantification spans many facets in the nuclear industry, including system design and optimization, licensing, and probabilistic risk assessment [1]. SAS4A/SASSYS-1, developed and maintained by Argonne National Laboratory, is a system level safety analysis code for Sodium-cooled Fast Reactors (SFRs) [2]. The Dakota software, maintained by Sandia National Laboratory, is an uncertainty quantification and optimization toolkit that has been in development for over 20 years [3]. Dakota and SAS4A/SASSYS−1 have recently been coupled via a Python interface to extend the capabilities of the Argonne SFR code for transient safety analyses. In uncertainty quantification mode, Dakota samples user-specified parameters, performs SAS4A/SASSYS−1 transient simulations with those parameters, and quantifies statistical metrics during post processing. Several sampling-based techniques were applied to propagate uncertainties in the transient simulations. The results were compared against those obtained by using a similar uncertainty quantification toolkit, RAVEN [4]. In addition to traditional sampling techniques, more advanced uncertainty quantification methodologies supported by Dakota were explored, including the Importance Sampling method and Reliability Method. These techniques were developed for Dakota to reduce the computational costs when the problem involves a large number of uncertainties. Dakota is also capable of design optimization for both local and global optima; the transient simulations were chosen to demonstrate the optimization capability. A few optimizers were tested in this paper with the consideration of efficiency. It should be noted that many of the uncertain parameters and the associated bounds in this study are chosen only for demonstration purposes and problem simplification, and are not rooted in a mechanistic uncertainty analysis.

II. DAKOTA AND SAS4A/SASSYS-1 COUPLING

A Python interface has been developed to couple Dakota with SAS4A/SASSYS-1 at Argonne. The Dakota executable is available pre-compiled via the Sandia National Laboratory website [3], and coupling with SAS4A/SASSYS-1 (or any software) is accomplished via a black-box interface. Dakota supports the invocation of a simulation code by either direct linkage or a system call. During the system call, the external code is initiated and data communication between Dakota and SAS4A/SASSYS-1 occurs through parameter and response files. Because the system call is more straightforward, it is applied to invoke the SAS4A/SASSYS-1 simulations in this study. Uncertain parameters are identified in the SAS4A/SASSYS-1 input template and replaced with the values generated by Dakota. The response values of interest from the SAS4A/SASSYS-1 simulation are saved for processing by Dakota. Fig. 1 illustrates this coupling scheme.

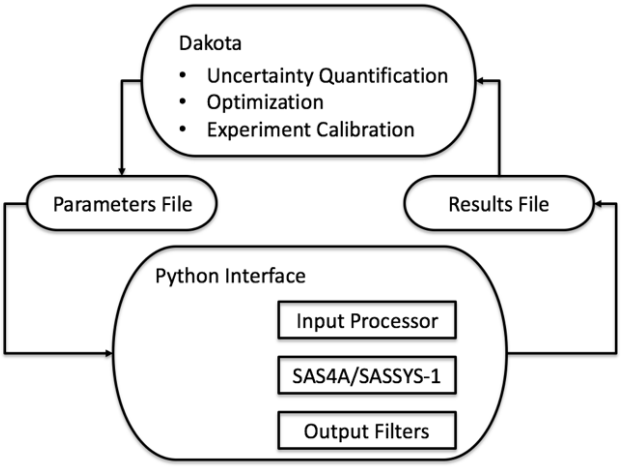

Fig. 1. Dakota and SAS4A/SASSYS-1 Coupling Scheme

A Dakota input file defines the method, variables, interface, and responses for the uncertainty quantification and design optimization. The sampling method or optimization functions are identified in the method section. Uncertain variables, probability distributions, and upper and lower bounds are specified in the variable section. The interface section defines the driver file name, the parameter file for the random values generated by Dakota, the SAS4A/SASSYS-1 input template, and the response file for saving the SAS4A/SASSYS-1 simulation results. The interface searches for the uncertain variables in the input template file and replaces them with the values generated by Dakota to create a new SAS4A/SASSYS-1 input. The total number of the responses is specified as Dakota input and the target responses along with the selection criteria are defined in the Python interface.

After the SAS4A/SASSYS-1 simulation finishes, the Python interface converts the binary SAS4A/SASSYS-1 output files (PRIMAR4.dat and CHANNEL.dat) into CSV files and searches for the target responses. The present interface has four output filters for the SAS4A/SASSYS-1 simulation results: 'max' for the maximum value, 'min' for the minimum value, 'begin' for the beginning value of the simulation, and 'end' for the value at the end of the simulation. Users choose the channels on which the filters are applied, where a user-defined SAS4A/SASSYS-1 "channel" can represent a single assembly or a group of assemblies with similar characteristics. If the channels are not specified, the interface will search for the target through all the channels in the system.

The responses of interest are written in a result file and returned to Dakota for the quantification of the statistical metrics. Means, standard deviations, and 95% confidence intervals are computed for each of the responses. In addition, Dakota calculates the most common statistics between uncertainties and responses of interest, such as the covariance, Pearson coefficient, simple, partial, and rank correlations. The Pearson coefficient is a measure of the linear correlation between two variables and its value is in a range between +1 to -1, inclusive. A Pearson coefficient with a large absolute value means that two variables are strongly correlated. A positive Pearson coefficient stands for a positive correlation while a negative value indicates that the two variables are inversely correlated.

III. ABTR TRANSIENT MODELS AND UNCERTAINTIES

The uncertainty quantification and design optimization capabilities were demonstrated for the Advanced Burner Test Reactor (ABTR) described in [5]. The ABTR is a conceptual design developed by Argonne during the Global Nuclear Energy Partnership's Advanced Burner Reactor Program. It features a thermal power of 250 MW and is intended to incinerate the trans-uranium from Light Water Reactors. The SAS4A/SASSYS-1 ABTR model for the transient analysis includes sodium pool as the primary heat transport system, a Direct Reactor Auxiliary Cooling System (DRACS) for decay heat removal, and two Intermediate Heat Exchangers (IHXs) connected to the intermediate loops.

Two unprotected transient events were considered in this study to evaluate the impacts of the uncertainties on the safety margins and test the design optimization libraries in Dakota. The Unprotected Loss of Heat Sink (ULOHS) transient is initiated when the intermediate pumps trip and heat rejection via the steam generator is reduced to zero at the beginning of transient. The primary loop pumps do not trip and continue to operate in a nominal state throughout the simulation. During the ULOHS, the inlet coolant temperature increases, resulting in a negative reactivity feedback contribution due to radial core expansion that shuts down the reactor. Another transient utilized in this study is the Unprotected Transient Overpower (UTOP) when one or more control rods are accidentally withdrawn and the reactor scram systems fail to response. The SAS4A/SASSYS-1 UTOP model assumes that external reactivity of 30 cents is inserted over 15 seconds. During the transient, both radial core expansion and control driveline expansion contribute large negative feedbacks to compensate for the positive external reactivity.

The parameters in Table 1 were used to demonstrate the uncertainty quantification capability of the coupling. These uncertainties were selected primarily based on the reactivity responses during the ULOHS and UTOP events. For some oxide fueled cores, the Doppler effect contributes a large positive feedback during the ULOHS and therefore is considered here as well. Although the reactivity coefficients are usually correlated due to the nuclear data uncertainties [6], the above variables are assumed to be independent and they are uniformly distributed within 25% of their nominal values. It should be noted that these uncertainties and the associated bounds were selected for demonstration purposes. A more comprehensive uncertainty quantification study focusing on both reactivity coefficients and heat transport

parameters was conducted on the Experimental Breeder Reactor II Balance-of-Plant tests [7].

Table 1. Nominal Values of Uncertain Parameters for ABTR ULOH Transient [8]

Uncertain Parameters	Nominal
Vessel Length and Expansion Coefficient	1.46×10^{-4} m/K
Control Rod Drive Expansion Coefficient	2.0×10^{-5} K^{-1}
Control Rod Feedback Coefficient	-24.0 \$/m
Doppler Feedback Coefficient	-1.37×10^{-3} Δk/k
Radial Expansion Feedback Coefficient	-4.17×10^{-3} \$/K

The boiling margin is an important measure of the reactor safety during the transient, as sodium boiling can be correlated with fuel damage and will affect core reactivity. SAS4A/SASSYS-1 tracks the coolant temperature along with the saturation value on a channel basis so the boiling margin can be calculated accordingly. The peak fuel temperature of each channel reported by SAS4A/SASSYS-1 is also of particular interest, as this is a good indicator of the timing, magnitude, and location of fuel failure.

IV. RESULTS

1. Uncertainty Quantification

After coupling Dakota and SAS4A/SASSYS-1, the capability to perform uncertainty quantification was demonstrated for the advanced reactor system level safety analysis. The primary sampling techniques supported by Dakota include Monte Carlo (MC) sampling, Latin Hypercube Sampling (LHS), and Grid sampling. These basic sampling techniques are simple and straightforward approaches for uncertainty propagation. Moreover, when a large number of uncertainties are investigated simultaneously or the understanding of complex reactor system is incomplete, the number of evaluations required by these basic sampling techniques quickly becomes prohibitive and more advanced uncertainty quantification methods are required. Therefore, Dakota supports more robust methods for uncertainty propagation, including the Reliability Method and the Importance Sampling method for the failure analysis. In this study, both the basic and advanced methods were tested using ABTR transients.

A. Conventional Sampling-based Techniques

SAS4A/SASSYS-1 was coupled with RAVEN and the demonstration of the uncertainty quantification was published in reference [8]. The new coupling between SASSYS/SASSYS-1 and Dakota was applied to repeat the previous uncertainty quantification analysis. Both RAVEN and Dakota support the following three sampling techniques:

- **Grid Sampling method**: A N-dimensional grid is discretized into segments and each dimension is represented by an uncertain variable. Sampling is performed at each node of the grid and therefore all possible combinations of the uncertain variables are evaluated. The number of sample points required by grid sampling depends exponentially on the input dimension.

- **Monte Carlo method**: A random sampling is conducted based on a specific distribution between the lower and upper bounds on each of the input variables. This is the most straightforward approach for uncertainty propagation.

- **Latin Hypercube Sampling method:** A method explores the input space where the uncertain domain is subdivided into N segments [3]. The relative length of each segment is determined by the probability distribution of the corresponding uncertainty. Every subgroup of the uncertain variable is randomly assigned to a sample only one time. There is no restriction on the number of bins for each uncertainty, but LHS requires all the uncertain variables to have the same number of bins. The total number of samples equals the number of bins for each variable. According to the Dakota manual, LHS technique requires fewer samples than the MC method for the same statistical accuracy [3].

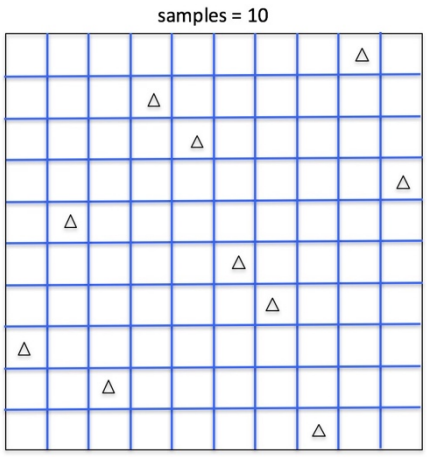

Fig. 2. Latin Hypercube Sampling Technique Supported by RAVEN and Dakota

The MC and LHS techniques were applied in Dakota with 1000 samples. The peak fuel temperature during the ABTR ULOHS transient was selected as the response of interest for the uncertainty quantification. The statistics generated from RAVEN and Dakota are compared in Table 2. The MC results from the two uncertainty quantification toolkits are in good agreement. As expected, the MC and LHS techniques can achieve the same accuracy as the grid sampling technique with a much smaller population.

Table 2. Uncertainty Quantification of the Peak Fuel Temperature in ABTR ULOHS from RAVEN and Dakota

	RAVEN		Dakota	
	Grid	MC	MC	LHS
Samples	2000	1000	1000	1000
Mean, K	822.8	822.9	822.8	822.8
Std. Dev.	1.27	1.19	1.18	1.18
Skewness	0.26	0.17	0.16	0.19
Kurtosis	2.23	-0.95	-0.99	-1.01
Cumulative Distribution Function for 5%, K	820.8	821.1	821.1	821.1
Cumulative Distribution Function for 95%, K	825.6	824.8	824.8	824.8

The impacts of the uncertainties on the peak fuel temperature are quantified by the Pearson Coefficients shown in Table 3. Since the radial core expansion contributes a large negative feedback during the ULOHS transient, a small change of the radial expansion feedback coefficient will impose a large effect on the net reactivity feedback. Therefore, both RAVEN and Dakota show a large positive Pearson value for the radial expansion feedback coefficients in Table 3. Control rod driveline expansion also provides a large amount of reactivity and therefore the related parameters have significant impacts as well. Since the ABTR design used in this study features metallic fuel, the feedback of the Doppler effects is small so that its impact is relatively insignificant. Fig. 3 and Fig. 4 show the impacts of the uncertainties on the minimum boiling margin and peak fuel temperature during the ABTR ULOHS transient.

Table 3. Comparisons of the Pearson Coefficients for Peak Fuel Temperature in ABTR ULOHS

Uncertain Parameters	RAVEN		Dakota	
	Grid	MC	MC	LHS
Vessel Length and Expansion Coefficient	0.09	0.11	0.08	0.06
Control Rod Drive Expansion Coefficient	-0.22	-0.17	-0.20	-0.20
Control Rod Feedback Coefficient	0.12	0.13	0.12	0.12
Doppler Feedback Coefficient	0.05	0.07	0.04	0.05
Radial Expansion Feedback Coefficient	0.96	0.97	0.97	0.97

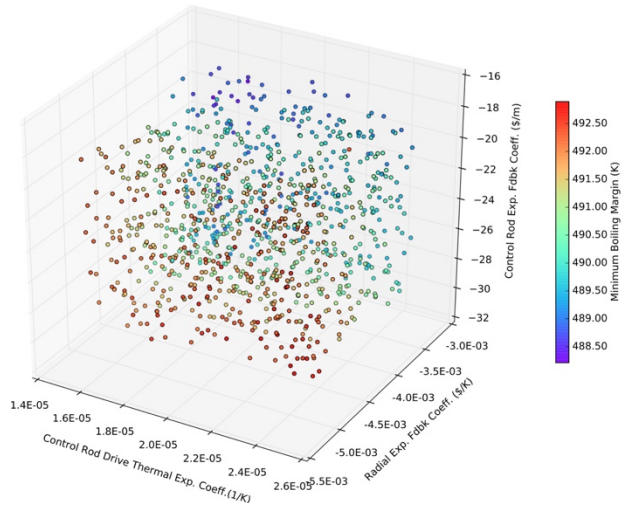

Fig. 3. Effects of the Three Most Important Uncertainties in Reactivity Feedback on Minimum Boiling Margin during ABTR ULOHS Transient by MC Sampling

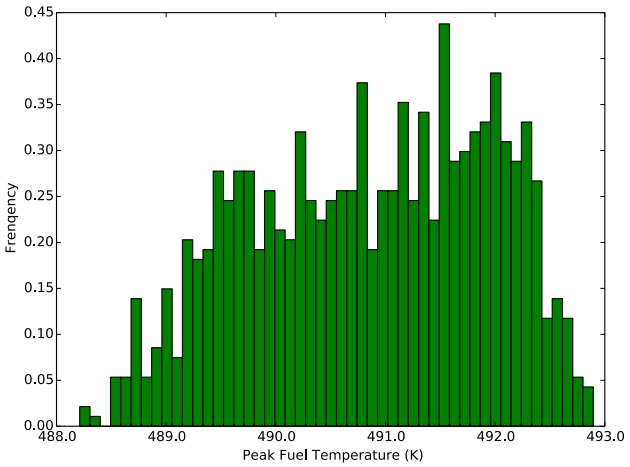

Fig. 4. Uncertainty Quantification of Peak Fuel Temperature during ABTR ULOHS Transient by MC Sampling

B. Importance Sampling Method

Importance Sampling provides another method to estimate the failure probability in a more efficient way than the traditional sampling-based techniques. This method preferentially samples on the important regions or the failure region of interest, and then appropriately weights the samples to obtain an unbiased estimate of the failure probability [3]. The Importance Sampling method is expected to be applicable for advanced nuclear systems when the safety margins are small. Instead of a large number of response function evaluations required by the conventional sampling-based methods, the Importance Sampling method reduces the computational cost by sampling near the failure region on the uncertain domain.

The ABTR Unprotected Transient Overpower (UTOP) scenario was used to demonstrate the Importance Sampling method supported by Dakota-SAS4A/SASSYS-1. It was assumed that an external reactivity of between 10 cents and 70 cents is added to the core over a period of 5 to 100 seconds; all other systems operate in their nominal states for the duration of the transient. Uniform distributions were applied for both uncertainties. A failure region where the boiling margin is less than 400 K was selected for demonstration purposes and problem simplification. The Importance Sampling method involves two steps: an initial Latin Hypercube Sampling is performed to generate the importance density, shown as the background in Fig. 5; successive samples are then centered around the points near the failure region. As shown in Fig. 5, the Importance Sampling preferentially focuses on the area where the boiling margin is below 400K and computes the failure probability of 10.5% based on the specified uncertainty domain.

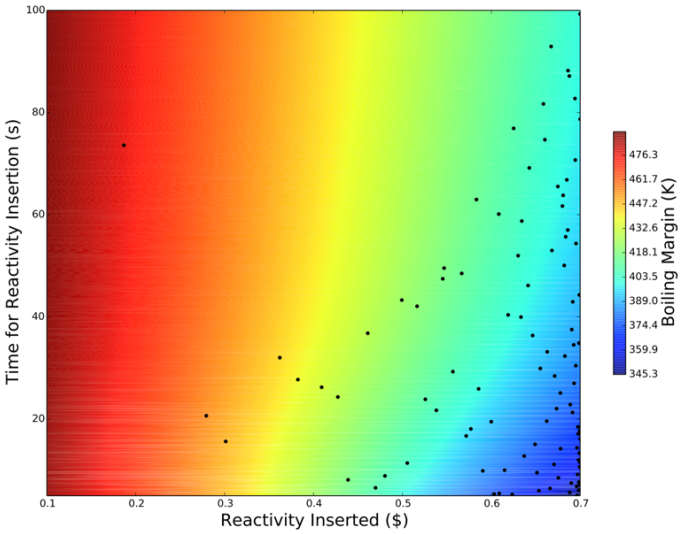

Fig. 5. Importance Sampling Approach for the Boiling Margin Below 400K

C. Reliability Method

The Reliability Method provides an alternative approach to the conventional sampling-based techniques when the uncertainty quantification analysis is computationally demanding. The algorithm of the Reliability Method was developed to compute the statistics in the tails of the response distribution in a more efficient way than sampling-based approaches. The Reliability Method addresses the problem to locate the most probable points and integrate the approximate probabilities. Given a set of uncertain variables and specified distributions, the probability that the response function is below or above a certain level is calculated [3]. In advanced nuclear system safety analysis, the Reliability Method can be applied to efficiently identify the region within a certain confidential interval. The Cumulative Distribution Function (CDF) of the safety metrics, such as boiling margin, can be calculated by the Reliability Method.

An ABTR UTOP transient was used to demonstrate the Reliability Method in the Dakota-SAS4A/SASSYS-1 package. It is assumed that external reactivity of between 10 cents and 70 cents is added to the core over a period of between 5 and 100 seconds, while all other systems operate nominally for the duration of the transient. Uniform distributions are applied for both uncertainties. The margins to coolant boiling are considered here as the response of interest. The Reliability Method in Dakota generates the approximate values of the cumulative distribution functions for the prescribed response levels in a range from 420K to 485K, as shown in Fig. 6. Based on the uncertainty distributions and their upper/lower bounds, the probability that the minimum coolant boiling margin is less than 420K during the ABTR UTOP transient is expected to be 28.4%.

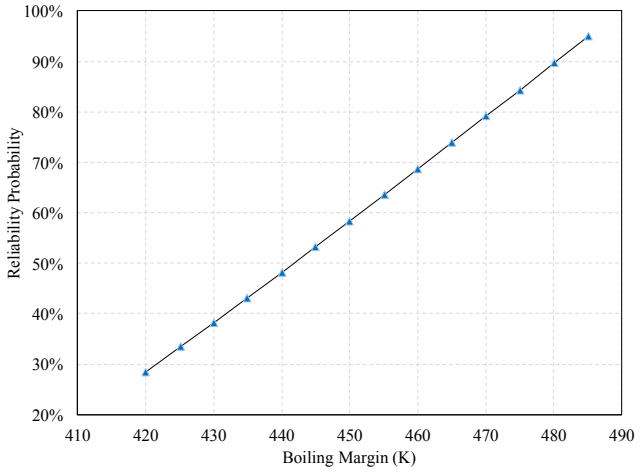

Fig. 6. Reliability Probability of the Coolant Boiling Margin for ABTR UTOP Transient by the Reliability Method

2. Optimization Capability

The early development of the Dakota software primarily focused on optimization applications. Dakota utilizes a variety of optimizers to minimize (or maximize) the objective functions while satisfying user-defined constraints. The coupled Dakota and SAS4A/SASSYS-1 package was tested for design optimization, which has the potential to improve the safety performance of advanced reactor designs. The primary approaches available in Dakota are gradient-based or derivative-free methods. Gradient-based optimizers are the most efficient way to navigate to a local optimum in situations where gradients can be computed analytically and efficiently [3]. Since the derivatives of the simulation results from SAS4A/SASSYS-1 are not available, the gradient-based approach is not applicable for design optimization by the Dakota-SAS4A/SASSYS-1 package.

Several derivative-free methods were chosen to demonstrate the automated optimization capability. The Pattern Search (PS) and Evolutionary Algorithm (EA)

methods were applied for the local and global optimum of the SAS4A/SASSYS-1 results, respectively. In order to reduce the computational cost for global optimum, a hybrid method combining the pattern search and evolutionary algorithm methods was tested as well.

The ABTR ULOHS transient was used to explore the optimization capabilities of the Dakota-SAS4A/SASSYS-1 package. It was assumed that peak fuel temperature during the ULOHS transient can be minimized by perturbing the Doppler feedback coefficient and radial expansion feedback coefficient. The radial expansion feedback was selected because of its significant impact on the transient; the Doppler reactivity feedback is a parameter sensitive to the fuel temperature. The upper and lower bounds of the two parameters are specified in Table 4. It should be noted that these parameters depend on the reactor design and usually are not independent. However, for problem simplification and demonstration purposes, it is assumed that we are able to perturb these two parameters freely.

Table 4 Design Constraints Used for the Dakota-SAS4A/SASSYS-1 Optimization

	Nominal	Upper Bound	Lower Bound
Doppler Feedback Coefficient, Δk/k	-1.373×10^{-3}	-1.028×10^{-3}	-1.713×10^{-3}
Radial Expansion Feedback Coefficient, $/K	-4.167×10^{-3}	-3.128×10^{-3}	-5.213×10^{-3}

A. Pattern Search Approach for Local Optimum

The Pattern Search (PS) approach is a derivative-free local method that can be applied to optimization problems. An optimizer, called "Coliny Pattern Search," is distributed within a collection of optimizers in Dakota [3]. The depiction of the pattern search algorithm is shown in Fig. 7. An initial guess is provided by users and the temporary optimum is found around the starting point. It executes successive iterations and makes progress towards an optimum. The algorithm is repeated until the convergence criteria are satisfied.

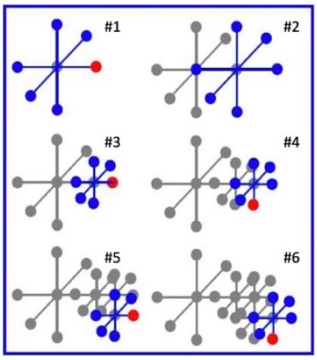

Fig. 7. Pattern Search Algorithm [3]

A demonstration test was conducted to find the optimized Doppler feedback coefficient and radial expansion feedback coefficient in the design domain identified in Table 4 such that the peak fuel temperature during the ABTR UTOP transient is minimized. Fig. 8 illustrates the searching path of the demonstration example. The optimizer was initiated at the nominal point (-1.37×10^{-3}, -4.17×10^{-3}) and finally converged to an optimum (-1.71×10^{-3}, -5.21×10^{-3}), which is the lower bounds of the design constraints. This result is in good agreement with the observations shown in Table 3, as more negative values for both Doppler feedback coefficients and radial expansion feedback coefficient will reduce the peak fuel temperature during the ULOHS transient.

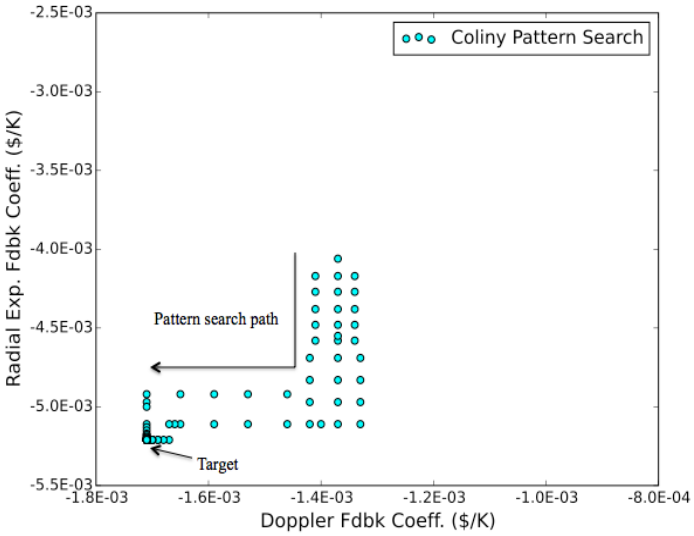

Fig. 8. Searching Path of the Pattern Search Optimizer for Local Optimum

B. Evolutionary Algorithm Approach for Global Optimum

The pattern search approach introduced above is best suited for efficient navigation to a local optimum. However, it depends on the user's guess and exhibits a limited ability to identify the global optimum when the behaviors of the responses are multimodal. Instead, Dakota supports the derivative-free global method Evolutionary Algorithm (EA). The evolutionary algorithm approach starts with a randomly selected population of design points in the domain; these points serve as "parents" and their values form a "genetic string", analogous to DNA in a biological system. The best design points (i.e. those with lower objective function values) are allowed to survive and reproduce. The evolutionary algorithm approach simulates the evolutionary process by employing the mathematical analogs on the global level and identifying the design points that minimize the objective functions [3].

A demonstration case was developed to find the global optimum (i.e. the minimum peak fuel temperature) by perturbing the Doppler feedback coefficient and radial

expansion feedback coefficient in Table 4. Fig. 9 shows the searching path for the demonstration case with the evolutionary algorithm method. In the first generation, there are fifty random points covering the design domain and only ten points are selected to reproduce; the algorithm executes successive generations and finally converges to the region around the target (-1.71×10^{-3}, -5.21×10^{-3}) after the seventh generation. This is consistent with the target obtained by the Pattern Search algorithm.

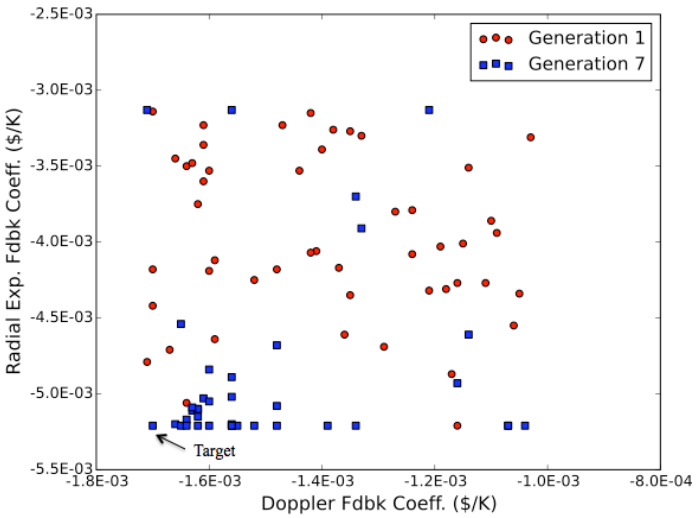

Fig. 9. Searching Path of Evolutionary Algorithm for Global Optimum

C. Hybrid Method for Global Optimum

The evolutionary algorithm method in Dakota is able to find the global optimum but requires extensive samples over the design domain. In order to reduce the computational cost of the evolutionary algorithm method, a hybrid method was applied to search for the global optimum. The hybrid method combines the global searching capability of the evolutionary algorithm approach with the efficiency of the pattern search method [3].

In the demonstration case, both the Doppler feedback coefficient and radial expansion feedback coefficient were perturbed to find the global optimum (i.e. the minimum peak fuel temperature) according to the design domain in Table 4. As shown in Fig. 10, the hybrid method runs two successive generations under the random sampling mode such that the point of global optimum has been identified to a smaller region of interest. Then, it performs efficient local searching for the target. The target (-1.71×10^{-3}, -5.21×10^{-3}) is consistent with those obtained by the Pattern Search and Evolutionary Algorithm methods.

Fig. 11 compares the evolution history and the number of SAS4A/SASSYS-1 simulations required for the optimum. In contrast to the pattern search algorithm, which is a local optimizer, the evolutionary algorithm approach searches for a global optimum but is more computationally expensive. It requires 50 samples in the first generation (each sample means one SAS4A/SASSYS-1 simulation) and 40 samples in the successive generations. In order to converge to the global optimum with the same accuracy, the evolutionary algorithm approach needs about three times more SAS4A/SASSYS-1 evaluations than the pattern search approach. Compared with the evolutionary algorithm approach, the hybrid method searches for the global optimum in a more efficient way and it requires 168 SAS4A/SASSYS-1 simulations. Therefore, the hybrid method is recommended for SAS4A/SASSYS-1 system optimization in the future.

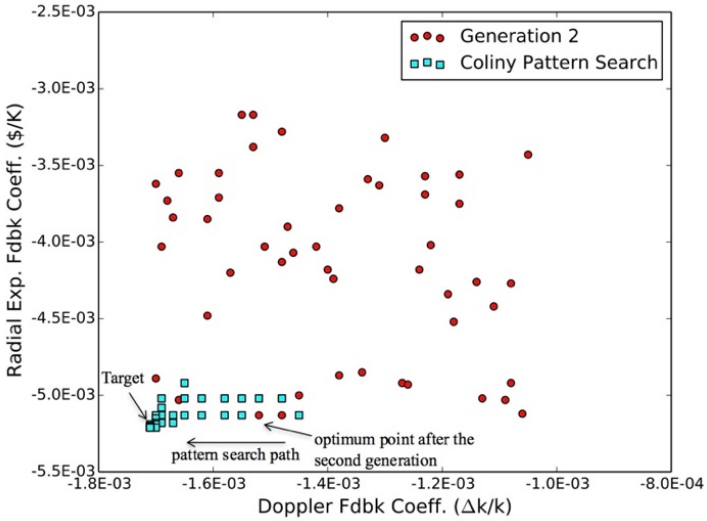

Fig. 10. Searching Path of Hybrid Method for the Global Optimum

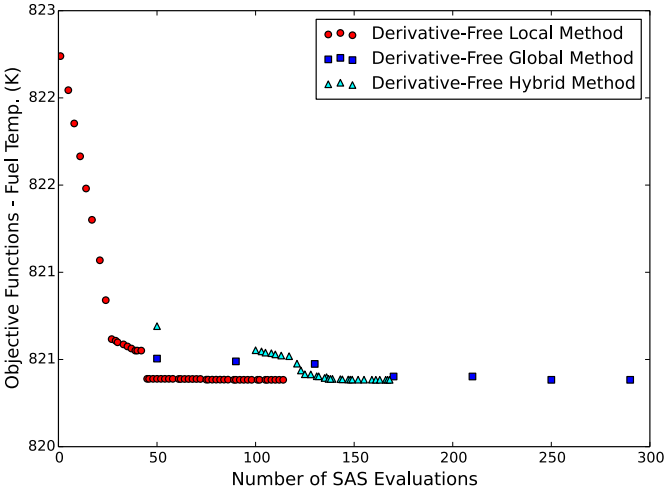

Fig. 11. Iteration History for Local, Global, and Hybrid Optimization Methods in Dakota-SAS4A/SASSYS-1 Package

V. CONCLUSIONS

Dakota and SAS4A/SASSYS-1 were coupled via a Python interface to meet an increased need to perform uncertainty quantification in the advanced reactor domain. Dakota was applied to sample user specified parameters, drive SAS4A/SASSYS-1 transient simulations, and quantify statistical metrics as part of post processing. The SAS4A/SASSYS-1 simulation for the ABTR ULOHS transient was used to demonstrate the capability for uncertainty quantification. Several sampling-based techniques (e.g. MC, LHS) were applied to propagate the uncertainties existing in the simulation. The statistics from uncertainty quantification analysis by Dakota were compared against those obtained by RAVEN and good agreement was observed. Additionally, Dakota is capable of advanced uncertainty quantification methodologies (e.g. Reliability Method, Importance Sampling method) and these methods were tested on the ABTR UTOP transient.

The Dakota toolkit also supports the optimization capability. For demonstration purposes, the Dakota-SAS4A/SASSYS-1 package was applied to find the minimized peak fuel temperature during the ABTR ULOHS by perturbing the Doppler feedback coefficient and radial expansion feedback coefficient. Both local and global optima can be found with different optimizers but searching for the global optimum is far more computationally expensive. A hybrid method that combines the local and global optimizers is recommended for the SAS4A/SASSYS-1 system optimization in the future due to its efficiency for the global optimum.

ACKNOWLEDGMENTS

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REFERENCES

1. L.L. BRIGGS, "Uncertainty Quantification Approaches for Advanced Reactor Analyses", ANL-GenIV-110, Argonne, IL, September 30, 2008.
2. T.H. FANNING, "The SAS4A/SASSYS-1 Safety Analysis Code System", ANL/NE-12/4, Argonne, IL, January 31, 2012.
3. B.M. ADAMS, et. al., "Dakota, A Multilevel Parallel Object-Oriented Framework for Design Optimization, Parameter Estimation, Uncertainty Quantification, and Sensitivity Analysis: Version 6.0 User's Manual," Sandia Technical Report SAND2014-4633, July 2014. Updated November 2015 (Version 6.3).
4. C. RABITI, et al., "RAVEN User Manual", INL/EXT-15-34123, Rev. 2 Draft, Idaho National Laboratory, May 2015
5. Y.I. CHANG, et. al., "Advanced Burner Test Reactor Preconceptual Design Report", ANL-ABR-1, Argonne, IL, September 5, 2006.
6. N.E. STAUFF, et. al., "Impact of Nuclear Data Uncertainties on the Performance of the Advanced Burner Reactor", *Proceeding of PHYSOR2016*, Sun Valley, Idaho, USA, 2016.
7. G. ZHANG, T. SUMNER, T. FANNING, "Uncertainty Quantification of EBR-II Loss of Heat Sink Simulations with SAS4A/SASSYS-1 and DAKOTA", *Proceedings of 2017 International Conference on Fast Reactors and Related Fuel Cycles*, Yekaterinburg, Russia, June 26-29 2017 (To Be Published).
8. A.J. BRUNETT, T.H. FANNING, "Uncertainty Quantification in Advanced Reactors: The Coupling of SAS4A/SASSYS-1 with RAVEN and Dakota", *Proceedings of ICAPP 2016*, San Francisco, April 17-20, 2016.