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RISK- AND COST-BASED SEISMIC DESIGN OPTIMIZATION OF ADVANCED NUCLEAR REACTOR SYSTEMS

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ABSTRACT

This paper demonstrates the seismic design optimization of a representative safety system in a nuclear power plant with the dual goals of minimizing overnight capital cost and meeting safety goals. The open source codes MASTODON and Dakota for seismic probabilistic risk assessment (SPRA) and optimization, respectively. A representative safety system with systems, structures and components (SSCs) that are common to safety-related nuclear structures is considered and sited at the Idaho National Laboratory site. Generic costs and cost functions are assumed for the SSCs of the safety system and the sum of the costs of the SSCs is minimized in the optimization process, while the risk of failure of the safety system is provided as a constraint. Results show that the optimization process reduces capital costs while automatically prioritizing the safety of SSCs that contribute most to the risk of the safety system.

INTRODUCTION

The high capital costs per constructed MWh of operating capacity of nuclear power plants (NPPs) have significantly deterred new nuclear construction in the United States over the last few decades (Buongiorno *et al.*, 2018). The uncertainty and site dependence of seismic hazard makes the cost of seismic design one of the most significant contributors to the overnight capital costs (OCC). While Stevenson (2003) found that this cost is around 10 - 20% of OCC at a site with a low to medium seismic hazard and a design PGA of 0.2-0.3g, anecdotal evidence indicates that it can be upwards of 30% at sites with a higher seismic hazard when both direct and indirect costs are included. The Facility Research Group (FRG) at the Idaho National Laboratory (INL) has been working with industry and academic partners to find solutions that lower capital costs of new-build plants while maintaining safety. These solutions include reducing conservatisms through simulating nonlinear soil-structure interaction (Bolisetti et al., 2017), deploying seismic isolation (Buongiorno et al., 2018; Yu et al., 2018), and optimizing seismic design for cost while meeting safety goals.

Design optimization is a routine goal of all branches of engineering. For example, the designs of buildings, bridges, commercial airliners, automobiles, cell phones, and computers are optimized to reduce the cost of fabricating or constructing each product, within the constraints of safety, regulations, and manufacturability. Because of the disciplines involved, the design optimization of an NPP can be considerably more complex, given the stringent regulations in the nuclear industry and the disparate collection of a large number of systems, structures and components (SSCs), including structural elements, and mechanical and electrical equipment, that comprise each NPP. However, given that the balance of plant (BoP: all SSCs except those involved in power generation, e.g., reactor vessel) contributes to a significant portion (~ 50%) of the capital cost of an NPP (see Stevenson (2003) and Buongiorno *et al.* (2018) for a description of relative costs of various equipment classes in an NPP), design optimization of BoP in NPPs should lead to a significant reduction in OCC.

The study presented in this paper is the first step in the design optimization of BoP and demonstrates an optimization of the seismic design of a generic safety system in an NPP. The optimization approach iteratively adjusts the seismic capacities of the various SSCs that comprise the system to calculate the optimal seismic capacities that result in the least capital cost and a risk of system failure that is smaller than a prescribed level. The optimization process uses the newly-implemented seismic probabilistic risk assessment (SPRA) capabilities of MASTODON (Coleman *et al.*, 2017), which is an open source finite-element and risk-analysis code developed by the FRG, together with a genetic algorithm (GA) implementation in the open source optimization code, Dakota (Adams *et al.*, 2014), developed at Sandia National Laboratory.

SEISMIC PROBABILISTIC RISK-ASSESSMENT

MASTODON performs SPRA calculations using the time-based methodology proposed by Huang *et al.* (2008) and Huang *et al.* (2011). This methodology (hereafter referred to as the Huang methodology) accommodates nonlinear response in the soil-structure system, unlike the traditional SPRA approach (EPRI, 2013), which assumes linear behavior throughout the model. The Huang methodology is therefore suitable for problems that include nonlinear soil-structure interaction (SSI), nonlinear site response, seismic isolation, and nonlinear structural response (which may occur in NPPs during beyond design basis shaking). A primary improvement in this methodology from the traditional SPRA is the usage of fragility curves for systems, structures and components (SSCs) that are functions of a local demand parameter such as, spectral acceleration at the point of attachment of an equipment. In a traditional SPRA approach, the SSC fragility curves are typically expressed as functions of peak ground acceleration (PGA).

The Huang SPRA methodology involves five steps, as illustrated in Figure 1. The first step is plant system analysis, which involves the development of event trees and fault trees that lead to an accident or an unacceptable event (such as core damage). Fault trees describe the logic leading to the occurrence of a top event from one or more basic events, which typically correspond to the damage or failure of an SSC, such as a pipe burst or a shear wall failure. For each of these basic events, a fragility curve is calculated, which describes the probability of the occurrence of the basic event conditioned upon a local demand parameter such as the story drift of a shear wall. An event tree describes the logic between several such top events leading to an accident or an unacceptable event. The second step involves a probabilistic seismic hazard analysis and the calculation of seismic hazard curves, which describe the mean annual frequency of exceedance (MAFE) of a particular ground motion parameter, such as PGA or the spectral acceleration at 0.1 sec. In the Huang methodology, the seismic hazard curve is divided into several intervals (or bins) spanning through the range of interest of the seismic hazard. Ground motions are selected and scaled for each of these bins such that they represent the seismic hazard of the bin as well as the uncertainty in the ground motion characteristics, such as frequency content. The third step involves probabilistic simulations of the structure using the ground motions selected in the previous step. These probabilistic simulations involve random sampling (using sampling procedures like Monte Carlo or Latin Hypercube) of the ground motions and properties of the soil-structure system and performing several (tens to hundreds) simulations. The results of these simulations are used to calculate the probabilistic demands (expressed as lognormal distributions) at the locations of SSCs corresponding to the basic events. In the Huang methodology, the demands from the tens or hundreds of simulations are expanded to hundreds of thousands of demands using the Yang *et al.* (2009) procedure, which conserves the statistical correlations between the various SSC demand distributions while expanding the demand datasets. The fourth step involves using these demands, along with the fragility curves calculated in the first step, to calculate the probability of failure of the SSCs conditioned upon the seismic demands. In the fifth step, these conditional probabilities of failure, along with the event trees and fault trees developed in the first step, are used to calculate the probability of occurrence of the accident or unacceptable event for each hazard bin. Such a calculation is referred to as fault tree analysis (FTA) and can be performed either using a closed-form solution, or through Monte Carlo simulations using the expanded demand datasets calculated in the previous step. While the closed-form solutions are computationally inexpensive, they also assume that the demands from various SSCs are statistically independent. However, the Monte-Carlo simulations proposed by the Huang methodology do not require this assumption. Yu *et al.* (2018) compared the results calculated using the closed form solutions and Monte Carlo simulations for a simple fault tree and found that the results are similar for the problem considered in their study. The FTA is repeated for all the hazard bins of step 2 and the probability of each bin is multiplied with the corresponding mean annual frequency of shaking (from the hazard curve) to calculate the risk contribution from each bin. The total risk of accident or unacceptable performance is then calculated as the sum of the risk contributions.

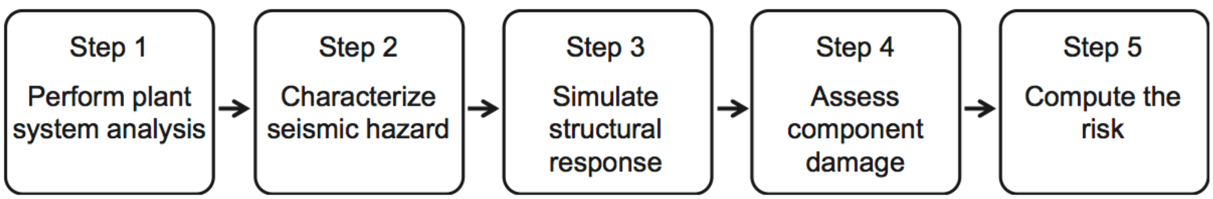


Figure 1: The SPRA methodology (Huang *et al.*, 2008; Huang *et al.*, 2011)

Implementation of the Huang SPRA methodology in MASTODON

The Huang SPRA methodology is implemented in MASTODON, both as a Python module and as a part of the source code (written in C++). While the inclusion in the source code provides a continuous integration between the finite-element simulations and SPRA, the Python module provides the flexibility to perform standalone SPRA in a more interactive environment. Both the Python module and the source code offer the capability to perform steps 3, 4, and 5 of the Huang SPRA methodology illustrated in Figure 1. The integration of SPRA in MASTODON and a description of the capabilities is presented in Figure 2.

MASTODON inputs the ground motions selected and scaled in step 2 and uses the stochastic tools module of the MOOSE framework to sample the properties of the finite element model along with the ground motions and run probabilistic simulations. Currently, it includes the Latin Hypercube and Monte Carlo samplers and is capable of efficiently parallelizing the probabilistic simulations amongst hundreds or thousands of processors. MASTODON also inputs the number of bins in the hazard curve, and postprocesses the probabilistic demands at SSC locations for each of these bins. Using the fragility curves (or capacity distributions, i.e., the probability of failure of the SSC given a local demand parameter) for each SSC provided by the user, MASTODON then calculates a probability of failure conditioned upon seismic shaking for each bin. A lognormal distribution is fit into these probabilities of failure to calculate an ‘enhanced fragility’, which describes the probability of failure of the SSC conditioned upon the seismic input to the plant. These enhanced fragilities are then used in the FTA to calculate the system fragility. The system fragility is then convolved with the seismic hazard according to step 5 of the Huang SPRA methodology (and also consistent with traditional approaches) to calculate the system risk.

Fault tree analysis and quantification in MASTODON can be performed both using closed-form solutions as well as Monte Carlo simulations. Currently, MASTODON is limited to the quantification of one fault tree at a time and does not analyze event trees. The closed-form solutions for FTA in MASTODON are calculated using the same approach used by the industry-standard probabilistic risk assessment (PRA) code, Saphire (USNRC, 2011) developed by INL for the United States Nuclear Regulatory Commission (USNRC). Saphire uses the MOCUS (Method for Obtaining Cut Sets) algorithm (Fussel and Vesely, 1972; Smith and Wood, 2011) to perform FTA and calculate the minimal cut sets for each fault tree. A minimal cut set is a combination of basic events, which, when occur together, will lead to occurrence of the top event of the fault tree. Generation of cut sets using MOCUS is a recursive calculation involving various Boolean operations and basic set theory. A detailed description of this cut set generation procedure is provided in the Saphire technical manual (Smith and Wood, 2011). Each fault tree can result in several minimal cut sets and the probabilities associated with these cut sets are calculated using the probabilities of basic events. This calculation is referred to as fault tree quantification. MASTODON, like Saphire, offers three methods of fault tree quantification: (1) rare event approximation, which involves the summation of the probabilities of all the minimal cut sets and is suitable for cut sets that have very small probabilities, (2) minimal cut set upper bound, which is an approximation of the probability of the union of all cut sets that provides a conservative estimate to the top event probability, and (3) min-max approach, which is an exact quantification of the fault tree and calculates the exact probability of the union of all the cut sets.

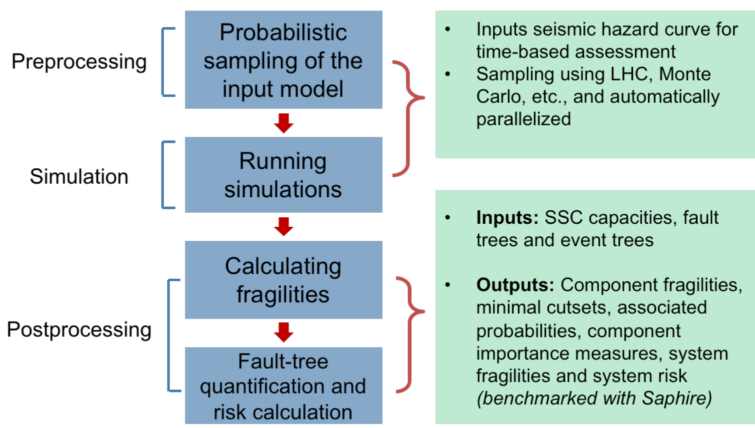


Figure 2: SPRA in MASTODON

RISK-BASED DESIGN OPTIMIZATION

The objective of the design optimization described here is to minimize the total capital cost of a safety system, while keeping the risk of unacceptable performance below a user-specified threshold. The safety system is assumed to include several SSCs that are vulnerable to earthquake shaking, and each of these SSCs has a fragility curve that is assumed to be representative of its seismic capacity. The fragility curve is represented by a lognormal distribution described by a median and a lognormal standard deviation. The cost of each SSC is assumed for this demonstration to be a function of its median fragility. The total cost of the safety system is then calculated as the sum of the costs of the SSCs. The risk of failure of the safety system is calculated using the fragilities of the SSCs and the fault tree of the system. For simplicity, it is assumed that the SSCs are only designed to meet the safety goals of the system and the SSCs do not have individual design constraints. The optimization process can also accommodate seismic isolation of individual SSCs, but that feature is not considered in the study presented in this paper. As the fragilities of the SSCs are reduced, the total cost of the system decreases, but the risk of an unacceptable event in the system increases, and beyond a certain point, will exceed the threshold. The optimization algorithm will result in an optimal set of SSC fragilities that result in minimum total cost, while maintaining risk below the threshold. Figure 3 describes the optimization problem of this study.

Optimization algorithms can be broadly classified into gradient-based algorithms, which search for a local or global minimum of an objective function by moving along the gradient of the function. Non gradient-based algorithms typically involve a logical and iterative search of the variable space, based on the value of the objective function and the adherence to the constraints of the optimization problem. Although gradient-based algorithms are fast, and assure the best optimal solution to a problem, they also require the objective functions to be continuous and differentiable. Non-gradient-based algorithms deploy numerically-based, *brute force*, approaches that are slower than gradient-based counterparts, and although their use may not result in the optimal solution, they almost always converge to an engineering solution that is better than the initial solution. Some algorithms provide multiple solutions, from which users can choose a solution of their choice. Non-gradient-based algorithms are also a lot more versatile and can input discrete variables (e.g., wall thicknesses) and characteristic variables (e.g., seismically isolated or non-isolated) that make them highly useful. Accordingly, a widely-used, non-gradient-based approach, the genetic algorithm, is used for optimization in this study. The algorithm is implemented here using the open-source optimization software, Dakota.

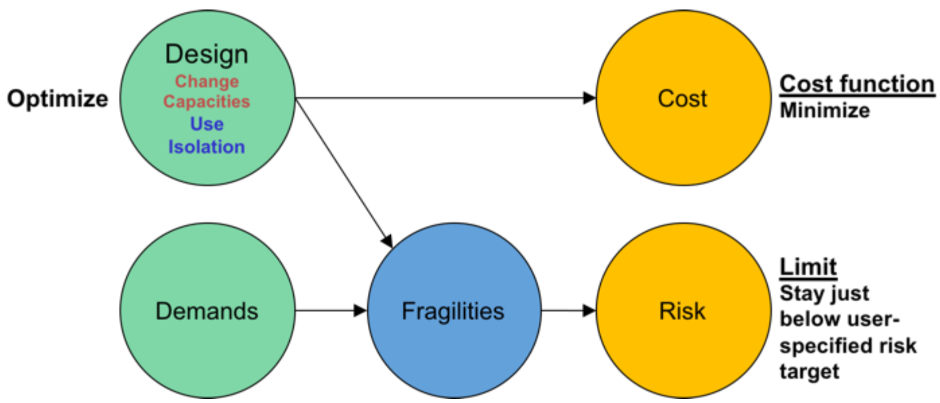
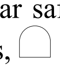


Figure 3: Illustration of the optimization problem of this study

Development of a representative PRA model

A representative safety system developed by Yu *et al.* (2018) for a generic nuclear facility (GNF) is used for this study. The GNF is assumed to handle materials that need to be contained within the facility, and the failure of the safety system is assumed to cause unwanted release of the material into the environment, as shown in the event tree presented in panel a of Figure 5. Panel b of the same figure shows the fault tree of this system and is composed of eight SSCs: motor control center, batteries, coolant pump, air handler, duct, structure, pressure vessel and piping. These SSCs are representative of nuclear safety systems and are taken by Yu *et al.* (2018) from the EPRI SPRA Guide (EPRI, 2013). The symbols,  and  in this figure represent the AND and OR gates, respectively, and the circles denote basic events. Panel c of Figure 5 shows the input logic of this system supplied to the Python module of MASTODON for FTA and evaluation of the minimal cut sets (combinations of basic events that lead to system failure). The analysis results in seven minimal cut sets for this fault tree, as listed in Table 1. These minimal cut sets show that the failure of the structure, or any of the mechanical or electrical components, or the failure of the air handler and duct, together will lead to the failure of the safety system. This is also evident from the fault tree presented in Figure 5. The GNF is assumed to be located within the boundary of the Idaho National Laboratory (INL) and the corresponding seismic hazard curve at a period of 0.1 sec, calculated by Yu *et al.*

(2018) from United States Geological Survey (USGS) data, is used for this study. This seismic hazard curve is presented in Figure 4.

Table 1: Individual cut set probabilities calculated using MASTODON

Cut set	Probability	Contribution to risk (%)
Structure	2.79×10^{-7}	0.9
Coolant pump	1.07×10^{-6}	3.3
Pressure vessel	7.79×10^{-7}	2.4
Piping	1.32×10^{-6}	4.0
Motor control center	1.74×10^{-5}	53.4
Battery	1.17×10^{-5}	36.0
Air handler AND Duct	4.10×10^{-11}	<0.01
Total	3.06×10^{-5}	100

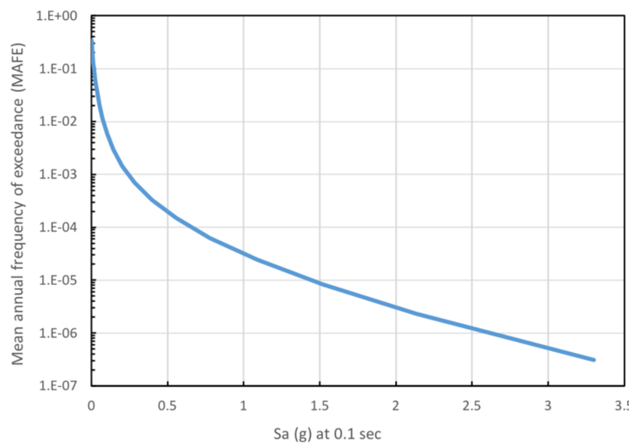
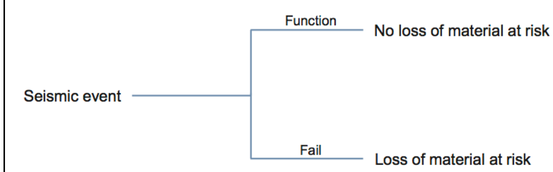


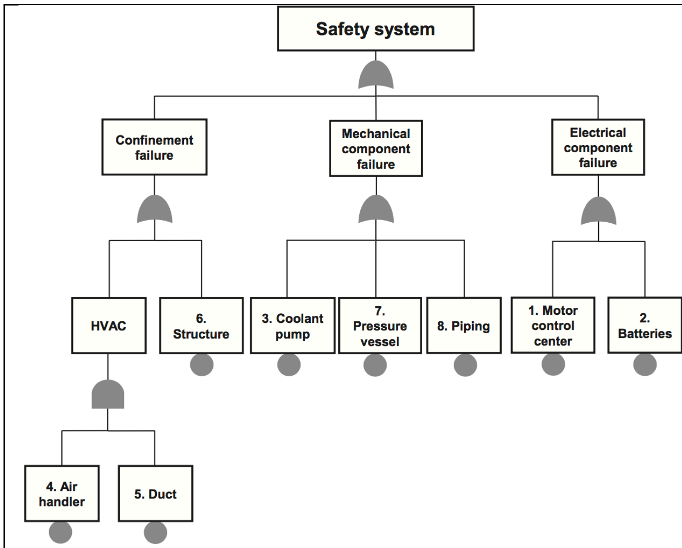
Figure 4: Seismic hazard curve for the spectral acceleration at 0.1 sec at the INL site (Yu *et al.*, 2018)

The seismic design of the safety system is taken as the set of fragilities for the selected SSCs. Generic fragilities of the SSCs (median, A_m, lognormal standard deviation due to uncertainty and randomness, β_u and β_r, respectively) are chosen from the fragilities recommended by the EPRI SPRA guide. The composite lognormal standard deviation, β_c, is calculated as the square root of the sum of the squares of β_u and β_r. To achieve a more representative value of risk, the medians of these fragilities are linearly scaled such that the risk of failure of the safety system is of the order of 10^{-5}. The fragilities so calculated are assumed to be the 'enhanced fragilities' in the MASTODON implementation of the Huang SPRA methodology, and therefore represent the probability of failure of the SSCs, given an intensity of shaking of the NPP. The optimization algorithm also requires a range of fragilities (or the design space) as an input. The fragility ranges provided in the EPRI SPRA guide are used for this purpose and are assumed to be sufficient for the purpose of this study.

Optimization of the seismic design of the safety system also requires estimates of costs of the SSCs as well as estimates of the increase of their costs with an increase in the seismic fragilities (i.e., the cost penalty for seismic design). A previous review of available literature by Bolisetti *et al.* (2016) and Yu *et al.* (2018) found that information regarding the seismic design costs in NPPs is scarce. The only available information is through surveys conducted by Stevenson (1981) in the 1980s, and anecdotal information from experienced professionals in the nuclear industry. Lal *et al.* (2019) are currently performing another survey to gather modern data on seismic design costs and to understand their variation with the design seismic demands. Due to the lack of modern data, generic SSC costs and cost functions (variation of SSC costs with median fragilities) are assumed for this study. A seismic cost penalty of around 50% is assumed for each SSC in the range of its design fragility. Although this is higher than the seismic design costs calculated by Stevenson (1981) or those suggested by professionals, it is deemed suitable for this demonstration study. To extend the optimization process to a diverse set of cost functions, alternate cost functions are assumed for the different SSCs. Step functions are assumed to describe the cost increases with median fragility of the motor control center, batteries, and the coolant pump. A linear function is assumed for the air handler, and quadratic functions are assumed for the structure and the pressure vessel. The cost of the distribution systems, piping and ducts, is assumed to be directly proportional to the square root of the median fragilities, as suggested by Stevenson (1981).



a. Event tree



b. Fault tree

```
system, OR, conf, mech, elec
conf, OR, hvac, struct
hvac, AND, airhand, duct
mech, OR, cpump, pvess, piping
elec, OR, mcc, batt
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c. Input file for fault tree analysis in MASTODON

Figure 5: Fault tree and event tree of the safety system used in this study, and the corresponding MASTODON input syntax for fault tree analysis

The fragility ranges, initial design fragilities, cost ranges, and initial costs used in this study are presented in Table 2. The table shows that the initial total cost of the safety system is about $98 million. Preliminary PRA in MASTODON showed that the risk of safety system failure is 3.06×10^{-5}. During PRA, MASTODON also evaluates the probabilities of the individual cut sets and their contribution to the total risk. This output is presented in Table 1, which shows that for the initial fragilities, the motor control center and the batteries dominate the system failure risk, with contributions of 53% and 36%, respectively. The table also shows that the cut set involving the failure of both the air handler and the duct (i.e., failure of the HVAC system) has a negligible contribution to the total risk.

Design optimization using MASTODON and DAKOTA

The single objective genetic algorithm, termed SOGA (Eddy and Lewis, 2001), available in Dakota is used for the design optimization of this study. SOGA, like all genetic algorithms, is an optimization approach inspired by the biological evolutionary process of natural selection, and can optimize both constrained and unconstrained problems, and can accommodate continuous, discrete, and characteristic design variables. For the optimization study of this paper, Dakota and the Python module in MASTODON are linked through Dakota's 'fork' interface, which enables the calculation of the objective functions and constraints using an external code (in this case, MASTODON's Python module). The Dakota input file includes the design space (ranges of fragilities of all SSCs), as well as the SOGA optimization parameters. For each evaluation in the optimization, Dakota samples the fragilities and supplies them to MASTODON, which then calculates the total cost of safety system (objective function) and the risk of failure of the safety system (constraint) that are again read by Dakota. The fragilities and costs presented in Table 2 are input to Dakota. A risk constraint of 10^{-5} is also provided to the optimization algorithm, so that it searches for solutions that result in a risk of safety system failure that is less this user-specified limit.

For simplicity, the risk calculation in the optimization iterations of this study only involve steps 4 and 5 of the Huang methodology. Since the fragilities are assumed to be functions of the shaking intensity in the hazard curve, structural response simulations are not performed. Nevertheless, given the modular implementation of the PRA process in MASTODON, this procedure can be easily extended to include the structural simulations and perform a more comprehensive optimization. The hazard curve is split into six bins, and the fault tree analysis and quantification are performed using the MOCUS method. For each bin, the probability of system failure is calculated and multiplied by the corresponding mean annual frequency to calculate the risk. The total system risk is then calculated as the sum of the risk in each of the six bins.

The optimization of this study started with a population of 50 randomly sampled possible solutions. This population is iterated through some biologically-inspired operations (mutation, crossover and replacement) by SOGA, and 50 such iterations are performed as the population converges close to the optimum solution. This convergence can be clearly seen in Figure 6, which shows that by the 50th iteration, the population converges to a single value of total cost and risk. The figure also shows that the risk of the optimal solution is almost exactly at 1×10^{-5}, which is the user-specified threshold input to Dakota.

Table 2: Fragilities and costs of SSCs

SSC	Median fragility, A_m (g)				Cost (USD M)			Optimized design	
	Lower bound	Initial design	Upper bound	β_c	Lower bound	Initial cost	Upper bound	Median Fragility (g)	Cost (USD M)
Motor control center	1.4	2.8	4.0	0.58	7.5	9.00	11.0	2.87	9.00
Battery	2.0	3.0	4.0	0.58	3.5	4.50	5.5	3.57	5.00
Coolant pump	3.0	4.0	5.0	0.50	15.0	18.00	21.0	3.50	15.00
Air handler	2.0	3.0	4.0	0.50	3.0	3.75	4.5	2.29	3.22
Duct	2.0	3.0	4.0	0.58	5.0	6.77	7.5	2.00	5.00
Structure	4.0	5.0	6.0	0.46	30.0	30.94	45.0	4.09	30.01
Pressure vessel	3.0	4.0	5.0	0.46	10.0	11.25	15.0	3.18	10.04
Piping	4.0	4.6	5.0	0.58	10.0	13.87	15.0	4.11	11.66
	Initial risk 3.06×10^{-5}				**Initial cost 98.08**			**Final risk 9.99×10^{-6}**	**Final cost 89.01**

Table 2 also presents the optimal solution calculated by Dakota, including the optimal SSC fragilities, the corresponding costs, total cost of the safety system and the risk of failure. The results show that the total cost is reduced by $9 million from the initial design (~10% reduction) to a total capital cost of $89 million, along with a reduction in the risk of system failure, which is a third of that of the initial design. A comparison of the initial and final costs shows that the fragilities of all the SSCs (and therefore the costs) are reduced, except for the motor control center and the battery. In fact, the fragilities of these components (and therefore the costs) are slightly increased from the initial solution. This is because, as seen in Table 1, the motor control center and batteries provide the highest contribution to the total risk, and the optimization algorithm indicates that greater investments in these components are warranted than in the remaining components. This result shows that, although the cost reductions may not be significant in this demonstration problem, the optimization process provides important insight into the safety system and informs the users on how to prioritize their investments in certain components, aiding them in their decision making.

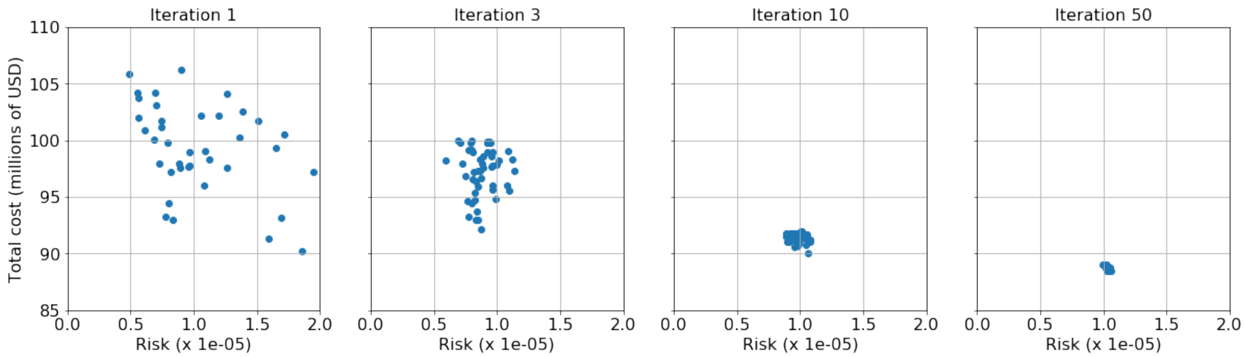

Figure 6: Progression of the genetic algorithm population through various iterations

SUMMARY AND FUTURE WORK

This paper presents a demonstration of a risk- and cost-based seismic design optimization of a representative safety system in an NPP populated with eight SSCs. Generic fragilities, costs, and cost functions (variation of seismic design cost with fragility) are assigned to these SSCs. The optimization process utilizes the recently implemented SPRA capability in MASTODON, along with an implementation of GA in the open-source optimization code, Dakota. Results of the optimization show a reduction in the overnight capital cost of the safety system from $98 million to $89 million (~10% reduction), while simultaneously reducing the risk to one-third that of the initial design. The results also show that the optimization algorithm automatically prioritizes the SSCs that contribute most to the total risk and encourages hardening these SSCs, while reducing the fragilities (and therefore cost) of the components that provide smaller contributions to the system risk.

Future work will involve the extension of this optimization process to safety systems that are more representative of advanced reactors, once better SSC fragility and modern cost data are available. The process will also be extended to include seismic isolation of individual SSCs, such that the algorithm automatically evaluates an optimal set of SSCs that need to be seismically isolated, along with adjusting the fragilities of other SSCs in order to minimize the total capital costs, while staying below the risk threshold.

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REFERENCES

Adams, B. M., Bauman, L. E., Bohnhoff, W. J., Dalbey, K. R., Ebeida, M. S., Eddy, J. P., Eldred, M. S., Hough, P. D., Hu, K. T., Jakeman, J. D., Stephens, J. A., Swiler, L. P., Vigil, D. M., and Wildey, T. M. (2014). "Dakota - A Multilevel Parallel Object-Oriented Framework for Design Optimization, Parameter Estimation, Uncertainty Quantification, and Sensitivity Analysis: Version 6.0 User’s Manual." SAND2014-4633, Sandia National Laboratory.

Bolisetti, C., Yu, C., Coleman, J. L., Kosbab, B., and Whittaker, A. S. (2016). "Characterizing the Benefits of Seismic Isolation for Nuclear Structures: A Framework for Risk-Based Decision Making." INL/EXT-16-40122, Idaho National Laboratory, Idaho Falls, Idaho.

Bolisetti, C., Talaat, M. M., Coleman, J. L., and Hashimoto, P. S. (2017). "Advancing Seismic Probabilistic Risk Assessment to Include Nonlinear Soil-Structure Interaction." *24th International Conference in Structural Mechanics and Reactor Technology, SMiRT24*, 20th - 25th August, 2017, Busan, Korea.

Buongiorno, J., Parsons, J., Corradini, M., and Petti, D. (2018). "The Future of Nuclear Energy in a Carbon Constrained World - An Interdisciplinary MIT Study." MIT Energy Initiative, Massachusetts Institute of Technology, Cambridge, MA, USA.

Coleman, J. L., Slaughter, A., Veeraraghavan, S., Bolisetti, C., Numanoglu, O. A., Spears, R., Hoffman, W., and Kurt, E. G. (2017). "MASTODON Theory Manual." INL/EXT-17-41930, Facility Risk Group, Idaho National Laboratory, Idaho Falls, ID, https://mooseframework.org/mastodon.

Eddy, J. E., and Lewis, K. (2001). "Effective Generation of Pareto Sets Using Genetic Programming." *Proceedings: ASME Design Engineering Technical Conference*, American Society of Mechanical Engineers.

Electric Power Research Institute (EPRI). (2013). "Seismic Probabilistic Risk Assessment Implementation Guide." *3002000709*, Palo Alto, CA.

Fussel, J. B., and Vesely, W. E. (1972). "A New Methodology for Obtaining Cut Sets for Fault Trees." *Transactions of the American Nuclear Society*, 15(1).

Huang, Y.-N., Whittaker, A. S., and Luco, N. (2008). "Performance Assessment of Conventional and Base-Isolated Nuclear Power Plants for Earthquake and Blast Loadings." MCEER-08-0019, Multidisciplinary Center for Earthquake Engineering Research, University at Buffalo, The State University of New York, Buffalo, NY.

Huang, Y. N., Whittaker, A. S., and Luco, N. (2011). "A Probabilistic Seismic Risk Assessment Procedure for Nuclear Power Plants: (I) Methodology." *Nuclear Engineering and Design*, 241, pp.3996-4003.

Lal, K., Parsi, S. S., Scott, D., Shirvan, K., Cohen, M., Kirchman, P., Kosbab, B., and Whittaker, A. (2019). "Cost Basis for Utilizing Seismic Isolation in Nuclear Power Plants." *Structural Mechanics in Reactor Technology (SMiRT 25)*, August, 2019, Charlotte, NC, USA.

Smith, C. L., and Wood, T. L. (2011). "Systems Analysis Programs for Hands-on Integrated Reliability Evaluations (SAPHIRE) Version 8." Volume 2: Technical Reference, NUREG/CR-7039, U.S. Nuclear Regulatory Commission, Idaho Falls, ID, USA.

Stevenson, J. D. (1981). "Evaluation of the Cost Effects on Nuclear Power Plant Construction Resulting from the Increase in Seismic Design Level." NUREG/CR-1508, U. S. Nuclear Regulatory Commission, Washington, D. C.

Stevenson, J. D. (2003). "Historical Development of the Seismic Requirements for Construction of Nuclear Power Plants in the U.S. and Worldwide and their Current Impact on Cost and Safety." *Structural Mechanics and Reactor Technology (SMiRT 17)*, August 17-22, Prague, Czech Republic.

United States Nuclear Regulatory Commission (USNRC). (2011). "Systems Analysis Programs for Hands-on Integrated Reliability Evaluations (SAPHIRE)." *NUREG/CR-7039*, Washington, District of Columbia.

Yang, T. Y., Moehle, J. P., Stojadinovic, B., and Der Kiureghian, A. (2009). " Performance Evaluation of Structural Systems: Theory and Implementation." *Journal of Structural Engineering*, 135(10), 1146-1154.

Yu, C.-C., Bolisetti, C., Coleman, J. L., Kosbab, B., and Whittaker, A. S. (2018). "Using Seismic Isolation to Reduce Risk and Capital Costs of Safety-Related Nuclear Facilities." *Nuclear Engineering and Design*, 326, pp. 268-284. dx.doi.org/10.1016/j.nucengdes.2017.11.016