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.

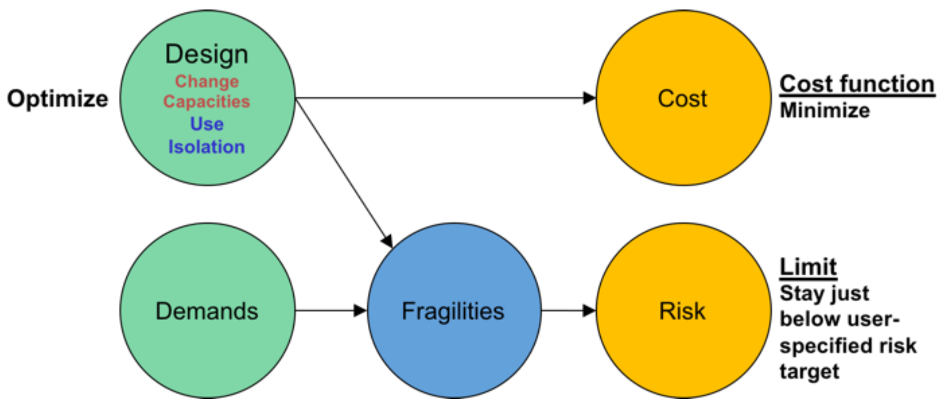


Figure 3: Illustration of the optimization problem of this study

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

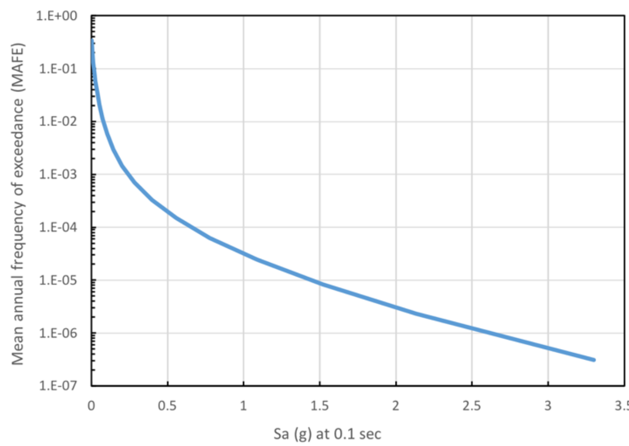
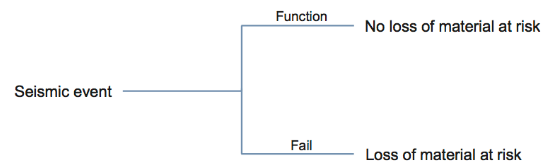


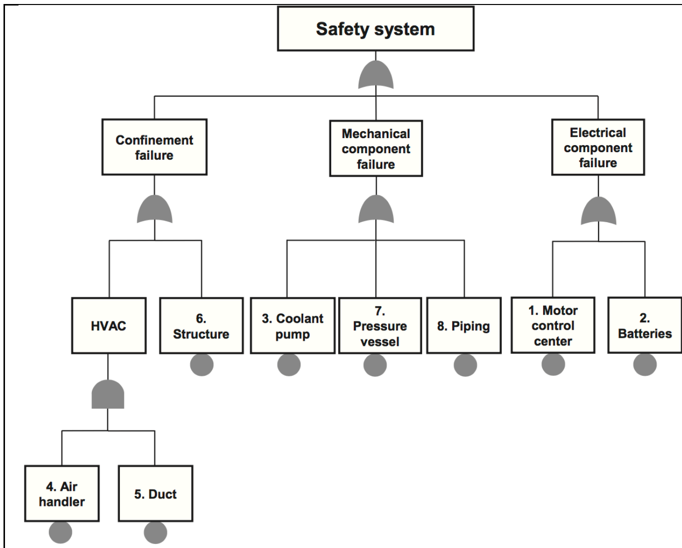
Figure 4: Seismic hazard curve for the spectral acceleration at 0.1 sec at the INL site (Yu *et al.*, 2018)

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
```

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.

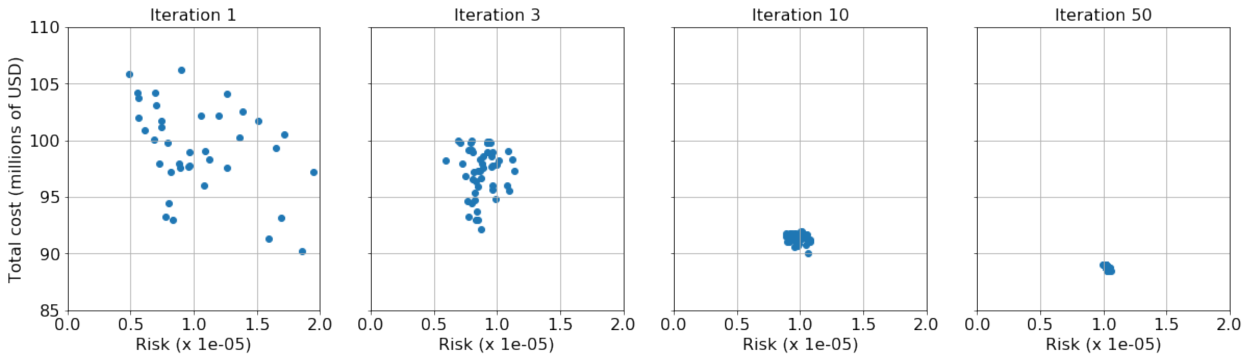


Figure 6: Progression of the genetic algorithm population through various iterations

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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