Genetic Algorithm Based Optimization for Nuclear Critical Experiment Design

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Motivation

- Nuclear data is the foundation of Monte-Carlo and deterministic neutron transport calculations
 - Used across all disciplines reactor physics, criticality safety, radiation detection etc.
- It is imperative that nuclear data is subject to rigorous verification and validation processes
 - Robust method is to design and operate critical experiments

<u>Goal</u>: Develop and implement a systematic methodology to design a critical experiment for cross section validation





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Optimization of Critical Experiments

- The nature of neutron transport calculation methods makes gradient free optimization more suitable
 - Discourages the computation of objective function gradients, if even possible
- Genetic algorithms are a popular and versatile gradient free method
 - Use evolutionary theory to seek a function optimum
 - Pros:
 - Versatile
 - Search a wide range of candidate design space
 - Cons:
 - Typically more computationally expensive than gradient based methods
 - Unconstrained technique require external constraint handling



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Genetic Algorithms







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Example: MOSES Critical Assembly

- <u>Mo</u>lybdenum <u>Sensitive Eigenreactor System</u>
 - Critical experiment designed using GA method
 - Purpose: Validation of molybdenum intermediate energy URR cross sections from 1 to 100 keV
 - Multiple operation configurations











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Example: MOSES Optimization

- Optimization Components:
 - <u>Objective function</u>: Peak Mo capture cross section sensitivity magnitude between 1 and 100 keV
 - <u>Design variables (4)</u>:
 - Plate thickness of moderator and Mo plates
 - Number of unit cells in each reactor unit
 - <u>Constraints</u>:
 - Experiment must be critical within \$0.80 excess reactivity
 - Upper unit weight less than 20,000 lbs., lower unit weight less than 2,000 lbs.
 - Fuel inventory
 - Comet vertical assembly machine geometric constraints
 - <u>Mathematical model</u>: MCNP[®] 6.1.1 Beta Monte-Carlo model





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Example: MOSES Optimization Results

MOSES Configuration 3 Parameters	
System Parameter	Value
Molybdenum Plate Thickness	0.55 in. / 1.3970 cm.
Teflon Plate Thickness	0.18 in. / 0.4572 cm.
Number of Upper/Lower Unit Cells	8 / 7
k _{eff}	1.00229 ± 0.00012
β_{eff}	0.00681 ± 0.00020
Excess Reactivity	0.34 ± 0.02
Stationary Weight	17211 lbs.
Mobile Weight	1183 lbs.
Intermediate Flux Fraction	0.455
Intermediate Fission Fraction	0.498
Max (n, y) Sensitivity Magnitude	0.01537
Max (n,n) Sensitivity Magnitude	0.00371
Total Max Sensitivity Magnitude	0.01908



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Conclusion and Future Work

- Genetic algorithms show good performance for autonomous design of critical experiments
 - Up-front cost of developing the autonomously-modifiable MCNP model but easy to extend to additional critical assemblies
 - GAs parallelize well, so computational cost can be decreased significantly using HPCs
- Future work:
 - Consideration of surrogate model optimization methods to increase efficiency
 - Tailor genetic algorithm to specifically handle critical experiments



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