Fluoride-Salt-Cooled High-Temperature Reactor Design Optimization with Evolutionary Algorithms
Preliminary Exam

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Outline

Overview

Additive manufacturing could radically transform reactor design.

I propose to:

- Model the Fluoride-Salt-Cooled High-Temperature Reactor's (FHR) neutronics and thermal-hydraulics and participate in the FHR benchmark
- Design an optimization tool that generates new 3D-printing enabled optimal reactor designs
- Use optimization tool to generate optimal non-conventional FHR designs

Figure 1: Example of a future reactor design with additively manufactured wavy flow channels

Why Generation IV Reactors?

- Energy use and production contribute $\frac{2}{3}$ of Greenhouse Gas emissions [2]
- Large scale emissions-free nuclear power deployment could significantly reduce GHG production but faces both cost and perceived safety challenges
- The Generation IV International Forum identified six systems that promise significant advances in safety, sustainability, efficiency, and cost over existing designs: GFR, LFR, MSR, SFR, SCWR, and VHTR.

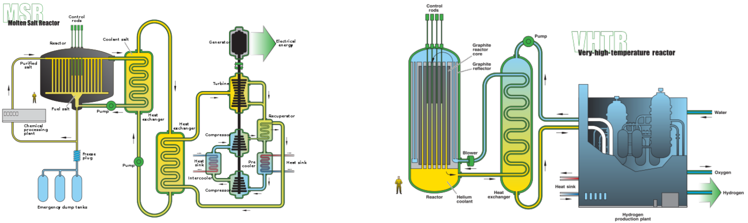


Figure 2: Left: Molten Salt Reactor System, Right: Very High-Temperature Reactor System [5].

MSRs and VHTRs

Molten Salt Reactor (MSR) System Advantages

- Molten Fluoride Salts: chemical stability, low vapor pressure at high temperatures, good heat transfer, resistance against radiation damage
- Inherent System Safety: passive cooling, fail-safe drainage

Very High Temperature Reactor (VHTR) System Advantages

- TRISO Fuel: withstands high burnup and temperature
- High Outlet Temperature: increases power conversion efficiency, reduces waste heat generation, enables high-temperature heat applications

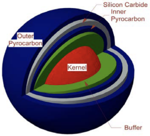


Figure 3: TRISO particle. Diameter: $\sim 8mm$

Fluoride-Salt-Cooled High-Temperature Reactor

FHR concept combines the best aspects of MSR and VHTR: low-pressure liquid fluoride-salt coolant and TRISO fuel

Fluoride-Salt-Cooled High-Temperature Reactor (FHR) Advantages

- Molten salt coolant vs. VHTR helium coolant: superior cooling, moderating properties, low operating pressure, large thermal margin
- TRISO fuel vs. MSR circulating liquid fuel: solid fuel cladding adds an extra barrier to fission product release

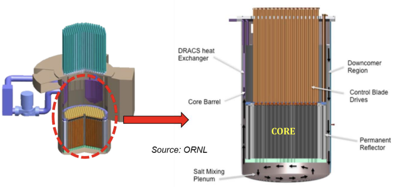


Figure 4: Advanced High Temperature Reactor (AHTR) schematic (left) and vessel (right) reproduced from [1].

Advanced High Temperature Reactor Design

- Design developed by Oak Ridge National Laboratory
- Prismatic FHR design with 252 hexagonal fuel assemblies consisting of 18 fuel planks arranged in 3 diamond-shaped sectors.

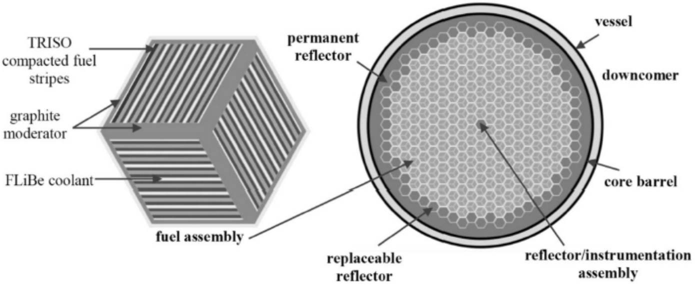


Figure 5: Advanced High Temperature Reactor fuel assembly (left) and core configuration (right) reproduced from [8].

Advanced High Temperature Reactor Geometry

The AHTR fuel has a *triple heterogeneity*: hexagonal fuel elements with fuel planks, and TRISO particles embedded in stripes within each plank.

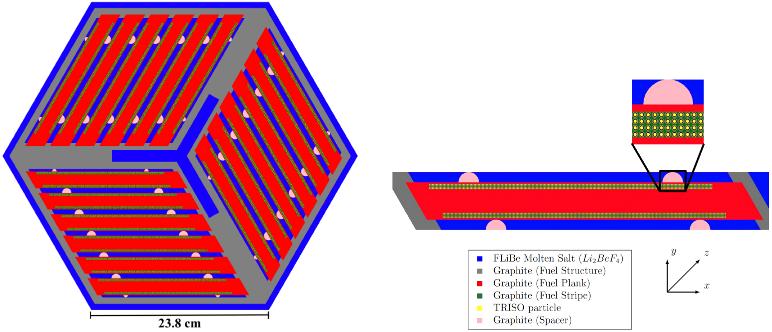


Figure 6: AHTR fuel assembly with 18 fuel plates arranged in three diamond-shaped sectors, with a central Y-shaped and external channel graphite structure.

FHR Benchmark

- The AHTR's fuel geometry's triple heterogeneity results in complex reactor physics and significant modeling challenges
- In 2019 the OECD-NEA initiated a FHR benchmark exercise. Its objective is to identify the applicability, accuracy, and practicality of the latest methods and codes to assess the current state of the art of FHR simulation and modeling

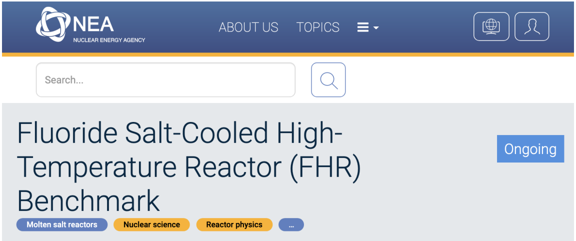


Figure 7: OECD NEA's FHR Benchmark [6].

Research Objectives: AHTR Model Development

Technical Gap

The triple heterogeneity introduced by the geometrically complex fuel assembly design makes accurate reactor physics simulations challenging.

Proposed Work Component 1: AHTR Model Development

- Further our understanding of the AHTR design's complexities through neutronics and thermal-hydraulics modeling
- Participate in the OECD-NEA's FHR Benchmark

Link to Reactor Optimization for Non-conventional Designs

- By participating in the benchmark, I ensure an accurate AHTR base model
- Thus, I can expect accurate answers for the optimized AHTR designs

3D Printing a Nuclear Reactor?

Impact of Additive Manufacturing Technology Advancements on Reactor Design Optimization

- With further advancement of additive manufacturing technologies, a reactor core could be 3D printed in the near future
- Leveraging additive manufacturing enables us to surpass classical manufacturing constraints and optimize for arbitrary geometries and parameters such as non-uniform channel shapes, and inhomogeneous fuel distribution throughout the core

Figure 8: Example of future reactor design with additively manufactured wavy flow channels

Evolutionary Algorithm Optimization

Evolutionary Algorithms for Reactor Design Optimization

- We can leverage evolutionary algorithm optimization to explore the large design space enabled by 3D printing to find global optimal designs
- Evolutionary algorithms have proven successful in optimizing multi-objective problems as they can find solutions at the global optimum and can be run in parallel
- Evolutionary algorithms imitate natural selection to evolve solutions

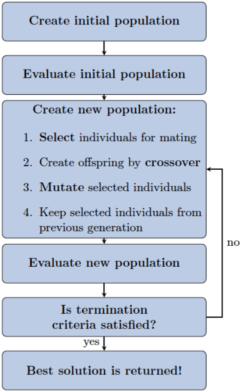


Figure 9: Evolutionary algorithm flow [9].

Research Objectives: Reactor optimization for non-conventional designs

Technical Gap

- Optimization tools for generating new reactor designs enabled by 3D printing do not exist
- Reactor optimization for non-conventional geometries and parameters has not been done

Proposed Work Component II: Reactor optimization for non-conventional designs

- Develop a tool that applies evolutionary algorithms with established nuclear software to optimize reactor design
- Demonstrate successful implementation of the optimization tool with OpenMC for single and multi-objective AHTR optimization of non-conventional geometries and fuel distribution

Summary

Additive manufacturing could radically transform reactor design.

Research Objectives: AHTR Model Development

- Further our understanding of the AHTR design's complexities through neutronics and thermal-hydraulics modeling
- Participate in the OECD-NEA's FHR Benchmark

Research Objectives: Reactor optimization for non-conventional designs

- Develop a tool that applies evolutionary algorithms with established nuclear software to optimize reactor design
- Demonstrate successful implementation of the optimization tool with OpenMC for single and multi-objective AHTR optimization of non-conventional geometries and fuel distribution

Outline

FHR Benchmark Specifications

- UIUC participates in the benchmark with OpenMC and using the ENDF/B-VII.1 material cross section library

Table 1: OECD NEA's FHR Benchmark Phases [6].

Phases	Sub-phases	Description
Phase I: fuel assembly	I-A	2D model, steady-state
	I-B	2D model depletion
	I-C	3D model depletion
Phase II: 3D full core	II-A	Steady-state
	II-B	Depletion
Phase III: 3D full core with feedback & multicycle analysis	III-A	Full core depletion with feedback
	III-B	Multicycle analysis

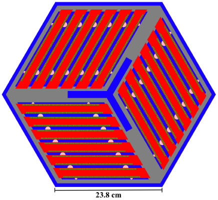


Figure 10: AHTR fuel assembly.

FHR Benchmark Specifications

- Only Phase I-A and I-B specifications have been released
- Benchmark participants must produce the following results for the 9 cases: k_{eff}, reactivity coefficients (β_{eff}, α_D, $\alpha_{T,FliBe}$, α_M), fission source distribution, neutron flux distribution, fuel assembly averaged neutron spectrum

Table 2: Description of the Fluoride-Salt-Cooled High-Temperature Reactor benchmark Phase I-A cases [1].

Case	Description
1A	• Reference case • 9 wt% enrichment • Hot full power • no burnable poison and control rod
2AH	• Hot zero power
2AC	• Cold zero power
3A	• Control rod inserted
4A	• Discrete europia burnable poison
4AR	• Discrete europia burnable poison • Control rod inserted
5A	• Integral (dispersed) europia burnable poison
6A	• Double TRISO particle fuel
7A	• 19.75 wt% enrichment

Optimization Tool's Design Goals

- The tool couples an evolutionary algorithm driver, Distributed Evolutionary Algorithms in Python (DEAP), with nuclear software, such as neutron transport OpenMC and thermal-hydraulics Moltres codes
- Design Goals: effective, flexible, open-source, parallel, reproducible

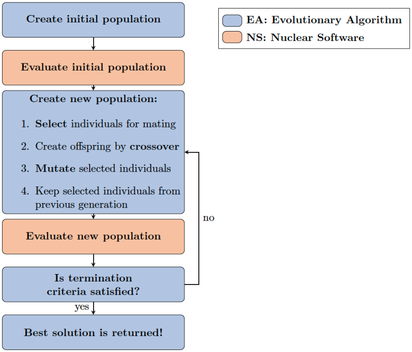
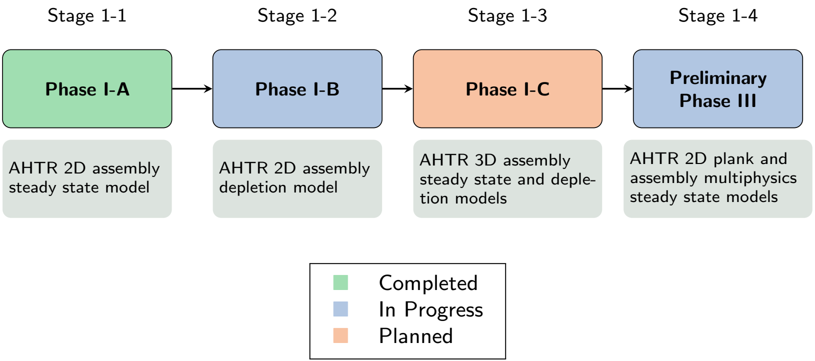


Figure 11: Optimization tool's flow.

Outline

Proposed Work's Component 1 Progress

AHTR Model Development for the FHR Benchmark



Completed Stage 1-1: FHR Benchmark Phase I-A Results

- FHR Benchmark Phase I-A: 2D assembly steady state model
- In a recently submitted ANS M&C 2021 conference paper we compared FHR benchmark participants' Phase I-A k_{eff} results. The standard deviation between participants for each case was in the 231 to 514 pcm range, acceptable and notably close given a blind benchmark

ANS M&C 2021 - The International Conference on Mathematics and Computational Methods Applied to Nuclear Science and Engineering · Raleigh, North Carolina · October 3–7, 2021

PRELIMINARY RESULTS OF THE NEA FHR BENCHMARK PHASE I-A AND I-B (FUEL ELEMENT 2-D BENCHMARK)

B. Petrovic[1*], K. Ramey[1], I. Hill[2], E. Losa[3], M. Elsawi[4], Z. Wu[5], C. Lu[5], J. Gonzalez[6], D. Novog[6], G. Chee[7], K. Huff[7], M. Margulis[8], N. Read[8] and E. Shwageraus[8]

Figure 12: FHR benchmark paper submitted to M&C 2021 [7].

Completed Stage 1-1: FHR Benchmark Phase I-A Results

Table 3: UIUC's FHR Benchmark Phase I-A results [3].

Case	Summary	k_{eff}*	Fuel $\frac{\Delta\rho}{\Delta T}$	FliBe $\frac{\Delta\rho}{\Delta T}$	Graphite $\frac{\Delta\rho}{\Delta T}$
1A	• Reference case • 9 wt% enrichment	1.39389	-2.24±0.15	-0.15±0.15	-0.68±0.15
	• Hot full power • no BP and CR				
2AH	• Hot zero power	1.40395	-3.14±0.15	-0.20±0.14	-0.85±0.14
2AC	• Cold zero power	1.41891	-3.36±0.14	-0.11±0.14	0.07±0.14
3A	• Control rod inserted	1.03147	-4.03±0.28	-0.83±0.27	-3.18±0.29
4A	• Discrete burnable poison	1.09766	-4.06±0.24	-1.55±0.23	-6.51±0.24
4AR	• Discrete BP • CR inserted	0.84158	-5.60±0.49	-1.78±0.46	-10.44±0.47
5A	• Dispersed burnable poison	0.79837	-5.09±0.40	-4.87±0.40	-22.99±0.38
6A	• Double TRISO particle fuel	1.26294	-4.46±0.19	0.16±0.20	-0.39±0.20
7A	• 19.75 wt% enrichment	1.50526	-2.49±0.13	-0.12±0.12	-0.62±0.12

BP: burnable poison, CR: control rod

* All k_{eff} values have an uncertainty of 0.00010.

- 500 active cycles, 100 inactive cycles, and 200000 neutrons
- UIUC's BlueWaters supercomputer with 64 XE nodes

Completed Stage 1-1: FHR Benchmark Phase I-A Results

Case 1A

- Reference case
- 9 wt% enrichment
- Hot full power
- no BP and CR

Case 3A

- Control rod inserted

Case 6A

- Double TRISO particle fuel

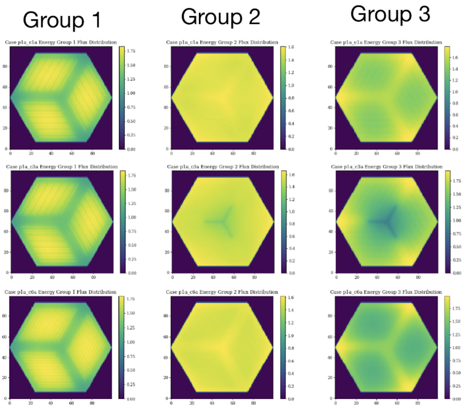


Figure 13: UIUC results: FHR Benchmark neutron flux distribution in 100 $\times$ 100 mesh for three coarse energy groups: Case 1A (above), Case 3A (middle), Case 6A (below). Energy group 1: $E > 0.1$ MeV, Energy group 2: $3 \times 10^{-6} < E < 0.1$ MeV, Energy group 3: $E < 3 \times 10^{-6}$ MeV.

In Progress Stage 1-2: FHR Benchmark Phase I-B Results

- FHR Benchmark Phase I-B: 2D assembly depletion model
- Benchmark participants are working on resolving differences in these results

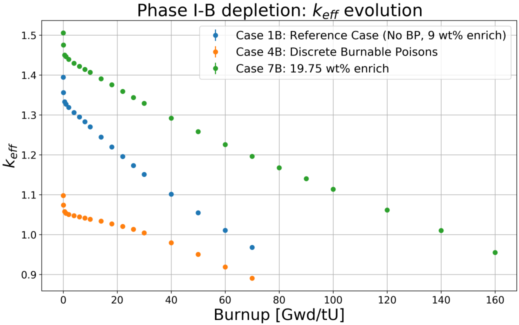


Figure 14: UIUC results: FHR Benchmark Phase I-B depletion k_{eff} evolution for Cases 1B, 4B, and 7B. Case 1B is the reference case, Case 4B is the discrete burnable poison case, and Case 7B is the 19.75% enrichment case. Error bars are included but are barely visible due to the low ~40pcm uncertainty.

Planned Stage 1-3: FHR Benchmark Phase I-C Planned Work

- FHR benchmark's Phase I-C extends the 2D assembly model from Phases I-A and I-B into a 3D assembly model
- Benchmark organizers will release the Phase I-C detailed specifications and required results in late 2021
- When the specifications are released, I will contribute Phase I-C results to the benchmark

In Progress Stage 1-4: FHR Benchmark Phase III Goals

- FHR Benchmark Phase III: 3D full core with feedback and multicycle analysis
- I will use the open-source MSR simulation tool, Moltres, to conduct AHTR multiphysics simulations for fuel slab and $\frac{1}{3}$ fuel assembly geometries
- AHTR Moltres simulations will capture thermal feedback effects, absent from the purely neutronics OpenMC simulations

In Progress Stage 1-4: Benchmark Phase III Preliminary Work

For successful AHTR Moltres simulation, I must establish suitable spatial and energy homogenization that preserves accuracy while maintaining an acceptable runtime

Spatial Homogenization

Fuel slab discretization into 13 cells: FLiBe, left graphite, right graphite, and ten fuel cells (each cell has a different packing fraction)

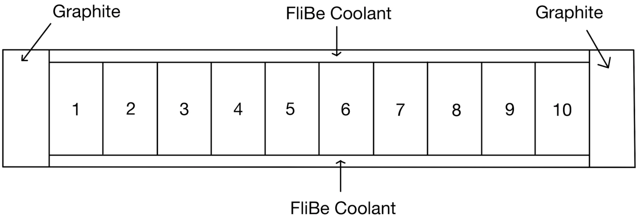


Figure 15: Straightened AHTR fuel slab spatially discretized into 13 *cells* for OpenMC multigroup calculation.

In Progress Stage 1-4: Benchmark Phase III Preliminary Work

Energy Homogenization

Group Boundaries [MeV]		
Group #	**Upper Bound**	**Lower Bound**
1	2.0000×10^{1}	9.1188×10^{-3}
2	9.1188×10^{-3}	2.9023×10^{-5}
3	2.9023×10^{-5}	1.8554×10^{-6}
4	1.8554×10^{-6}	1.0000×10^{-12}

Table 4: 4-group energy structures for AHTR geometry derived by [4].

Simulation Comparison: Continuous energy vs spatial and energy homogenized

Table 5: AHTR fuel slab's k_{eff} for case with continuous energy and space and case with spatial and energy homogenization.

Homogenization	k_{eff}	**Reactivity Δ [pcm]**	**Simulation time [s]**
None	1.40473 ± 0.00115	-	808
Spatial and Energy	1.40499 ± 0.00109	+26	50

Therefore, these homogenizations are suitable for generating group constants for a Moltres simulation.

In Progress Stage 1-4: Benchmark Phase III Planned Work

- Use these spatial and energy homogenization to set up a Moltres AHTR plank steady-state simulation
- Verify the Moltres model's neutronics parameters then run the steady state simulation to determine maximum temperature
- Test out energy and spatial homogenization methods for $\frac{1}{3}$ fuel assembly Moltres model

Outline

Proposed Work's Component 2 Progress

ROLLO (Reactor evOLutionary aLgorithm Optimizer) Tool Development and AHTR Non-Conventional Design Optimization

Stage 2-1	Stage 2-2	Stage 2-3	Stage 2-4
ROLLO v1.0 Build	**ROLLO v1.0 Single Objective Problem Demonstration**	**ROLLO Single Objective Problems**	**ROLLO Multi Objective Problems**
Build first version of ROLLO based on design specifications	• Demonstrate ROLLO's capabilities • Vary TRISO distribution in AHTR fuel slab to maximize k_{eff}	• Explore non-conventional reactor designs • Control Parameters: TRISO distribution, total fuel, and coolant channel shape • Objectives: minimize fuel amount, maximize heat transfer, minimize power peaking factor	

Completed
In Progress
Planned

Completed Stage 2-1: ROLLO v1.0 Build

```
{
    "control_variables": {
        "variable1": {"min": 0.0, "max": 10.0},
        "variable2": {"min": -1.0, "max": 0.0}
    },
    "evaluators": {
        "openmc": {
            "input_script": "openmc_inp.py",
            "output_script": "openmc_output.py",
            "inputs": ["variable1", "variable2"],
            "outputs": ["output1", "output2"]
        }
    },
    "constraints": {
        "output1": {"operator": [">=", "<"], "constrained_val": [1.0, 1.5]}
    },
    "algorithm": {
        "objective": ["min"],
        "optimized_variable": ["output1"],
        "pop_size": 100,
        "generations": 10,
        "mutation_probability": 0.23,
        "mating_probability": 0.46,
        "selection_operator": {"operator": "selTournament", "inds": 15, "tournsize":5},
        "mutation_operator": {
            "operator": "mutPolynomialBounded",
            "indpb": 0.23,
            "eta": 0.23
        },
        "mating_operator": {"operator": "cxBlend", "alpha": 0.46}
    }
}
```

Figure 16: ROLLO sample JSON input file.

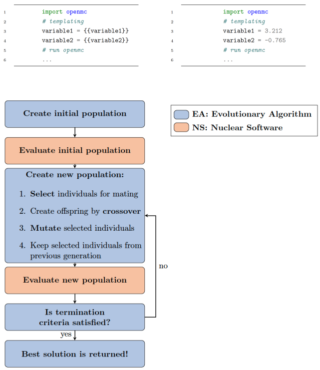


Figure 17: ROLLO's flow.

Completed Stage 2-1: ROLLO Class Architecture

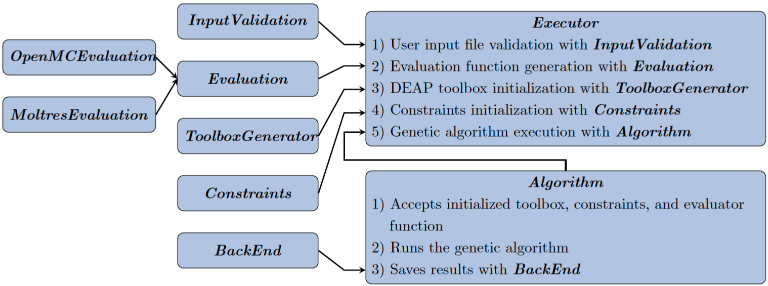


Figure 18: Visualization of ROLLO architecture.

Completed Stage 2-2: ROLLO v1.0 Demonstration

- Single objective design problem: maximize k_{eff} by varying TRISO particle distribution in an AHTR fuel slab while keeping total packing fraction constant
- A sine distribution governs the TRISO particle packing fraction's distribution across 10 cells:

$$PF(x) = (a \cdot sin(b \cdot x + c) + 2) \cdot NF$$

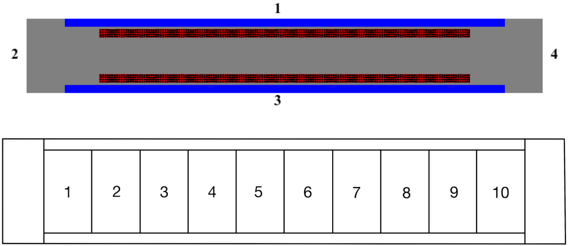


Figure 19: AHTR fuel slab spatially discretized into 13 cells (FliBe + left graphite + right graphite + varying TRISO particle distributions in 10 cells.)

Completed Stage 2-2: Problem Definition

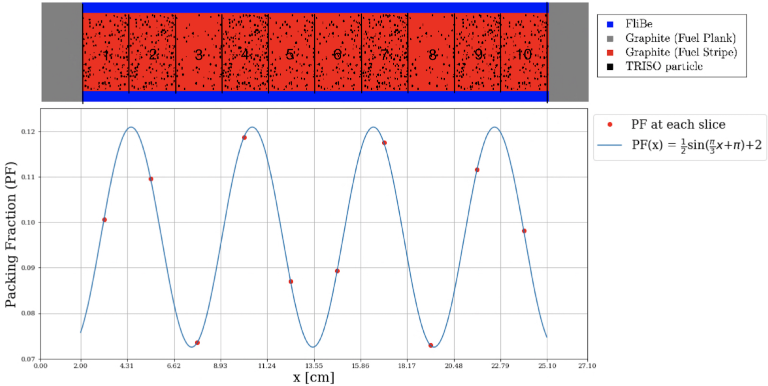


Figure 20: Above: AHTR fuel slab with varying TRISO particle distribution across ten cells based on the sine distribution. Below: $PF(x) = (0.5\ sin(\frac{\pi}{3}x + \pi) + 2) \times NF$ sine distribution with red points indicating the packing fraction at each cell.

Completed Stage 2-2: Problem Definition

```
{
    "control_variables": {
        "a": {"min": 0.0, "max": 2.0},
        "b": {"min": 0.0, "max": 1.57},
        "c": {"min": 0.0, "max": 6.28},
    },
    "evaluators": {
        "openmc": {
            "input_script": "ahtr_slab_openmc.py",
            "inputs": ["a", "b", "c"],
            "outputs": ["keff"],
            "keep_files": false,
        }
    },
    "constraints": {"keff": {"operator": [">="], "constrained_val": [1.0]}},
    "algorithm": {
        "objective": "max",
        "optimized_variable": "keff",
        "pop_size": 60,
        "generations": 10,
        "mutation_probability": 0.23,
        "mating_probability": 0.46,
        "selection_operator": {"operator": "selTournament", "inds": 15, "tournsize": 5},
        "mutation_operator": {
            "operator": "mutPolynomialBounded",
            "eta": 0.23,
            "indpb": 0.23,
        },
        "mating_operator": {"operator": "cxBlend", "alpha": 0.46},
    },
}
```

Figure 21: ROLLO JSON input file.

$$PF(x) = (a \cdot sin(b \cdot x + c) + 2) \cdot NF$$

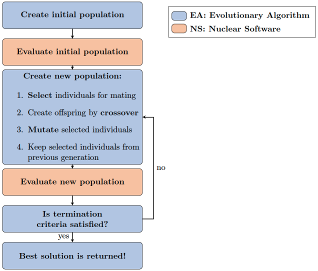


Figure 22: ROLLO's flow.

OpenMC runs each simulation with 80 active cycles, 20 inactive cycles, and 8000 particles to reach ∼130pcm uncertainty.

Completed Stage 2-2: Hyperparameter Search

- A good hyperparameter set guides the optimization process by balancing exploitation and exploration to find an optimal solution quickly and accurately
- I performed the hyperparameter search with a coarse-to-fine random sampling scheme
- I started with 25 coarse experiments and fine-tuned the hyperparameters with 15 more experiments

Completed Stage 2-2: Results from best hyperparameter set

Table 6: Control Parameters, k_{eff} results, and hyperparameter values for the best hyperparameter search experiments with the highest final generation $\overline{k_{eff}}$.

Control/Output Parameters	**Experiment 39**
$\overline{k_{eff}}$ [-]	1.40165
k_{effmax} [-]	1.40519
a [-]	1.989
b $[\frac{radians}{cm}]$	0.354
c [radians]	3.143
Hyperparameter	
Population size	60
Generations	10
Mutation probability	0.23
Mating probability	0.46
Selection operator	`selTournament`
Selection individuals	15
Selection tournament size	5
Mutation operator	`mutPolynomial Bounded`
Mating operator	`cxBlend`

Completed Stage 2-2: Results from best hyperparameter set

$$PF(x) = (a \cdot sin(b \cdot x + c) + 2) \cdot NF$$

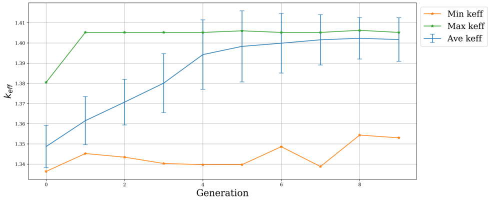


Figure 23: 39^{th} Experiment's k_{eff} evolution.

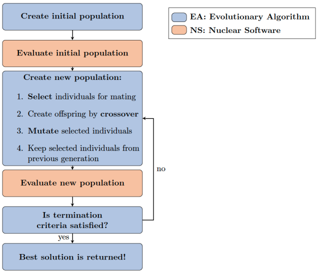


Figure 24: ROLLO's flow.

Completed Stage 2-2: Results from best hyperparameter set

TRISO particle packing fraction peaks in the center of the slab, showing that if the optimization problem focuses purely on the slab's neutronics by maximizing k_{eff}, the fuel tends to culminate in the middle.

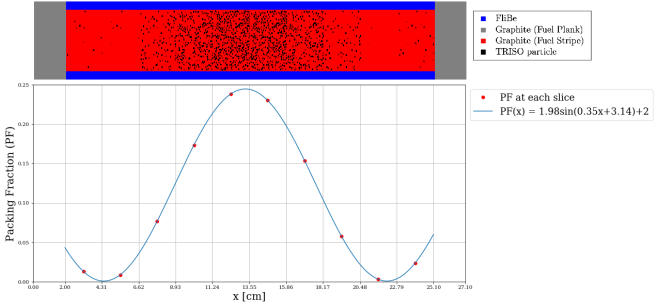


Figure 25: Experiment 39 packing distribution that produced $k_{effmax} = 1.40519 \pm 0.00130$. $PF(x) = (1.98\ sin(0.35x + 3.14) + 2) \times NF$ sine distribution.

Planned Stage 2-3: ROLLO Single Objective Problems

Center-peaking fuel density is nonideal for other key reactor core qualities, such as maximal heat transfer and minimal power peaking factor (PPF). Thus, the AHTR slab optimization problem must be extended to include these key reactor core qualities.

Objectives

Table 7: ROLLO optimization problem objectives with their quantification descriptions.

Objective	Quantification
Minimize fuel amount	Minimize total fuel packing fraction
Maximize heat transfer	Maximize ϕ_{total} in areas along FLiBe coolant
Minimize power peaking factor	Minimize $P_{high} - P_{low}$

Control Parameters

- TRISO particle packing fraction distribution $\rho_{TRISO}(\vec{r})$
- Total fuel packing fraction
- FLiBe coolant channel shape

Planned Stage 2-3: ROLLO Single Objective Problems

Table 8: Proposed ROLLO simulations for AHTR fuel assembly single objective optimization. PF: Total Fuel Packing Fraction, $\dot{Q}$: Heat transfer, PPF: Power Peaking Factor, $\rho_{TRISO}(\vec{r})$: Tristructural Isotropic (TRISO) particle distribution

Simulation	AHTR Geometry	Objectives	Varying Parameters
1	Single fuel slab	• $\max(k_{eff})$	• $\rho_{TRISO}(\vec{r})$
2	Single fuel slab	• $\max(\dot{Q})$	• $\rho_{TRISO}(\vec{r})$
3	Single fuel slab	• $\min(PPF)$	• $\rho_{TRISO}(\vec{r})$
4	Single fuel slab	• $\max(k_{eff})$	• FLiBe channel shape
5	Single fuel slab	• $\max(\dot{Q})$	• FLiBe channel shape
6	Single fuel slab	• $\min(PPF)$	• FLiBe channel shape

Planned Stage 2-4: ROLLO Multi-Objective Problems

Table 9: Proposed ROLLO simulations for AHTR fuel assembly multi objective optimization. PF: Total Fuel Packing Fraction, $\dot{Q}$: Heat transfer, PPF: Power Peaking Factor, $\rho_{TRISO}(\vec{r})$: TRISO particle distribution

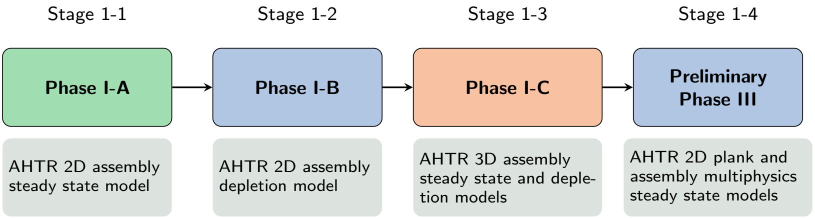
Simulation	AHTR Geometry	Objectives	Varying Parameters
7	Single fuel slab	• min(PF)) • max($\dot{Q}$) • min(PPF)	• $\rho_{TRISO}(\vec{r})$ • PF
8	Single fuel slab	• min(PF)) • max($\dot{Q}$) • min(PPF)	• FLiBe channel shape
9	Single fuel slab	• min(PF) • max($\dot{Q}$) • min(PPF)	• $\rho_{TRISO}(\vec{r})$ • PF • FLiBe channel shape
10	One-third fuel assembly	• max(k_{eff}) • max($\dot{Q}$) • min(PPF)	• $\rho_{TRISO}(\vec{r})$
11	One-third fuel assembly	• max(k_{eff}) • max($\dot{Q}$) • min(PPF)	• FLiBe channel shape
12	One-third fuel assembly	• max(k_{eff}) • max($\dot{Q}$) • min(PPF)	• $\rho_{TRISO}(\vec{r})$ • PF • FLiBe channel shape

Outline

Conclusion

AHTR Model Development for the FHR Benchmark

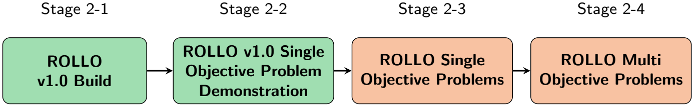
- Relevance
  - The triple heterogeneity introduced by the geometrically complex AHTR fuel assembly design makes accurate reactor physics simulations challenging
- Preliminary Results
  - I participated in Phase I-A and I-B (2D AHTR assembly steady state and depletion models) of the OECD NEA's FHR benchmarking exercise
- Planned Work
  - Submit Phase I-C Results (3D assembly steady state and depletion models)
  - AHTR Multiphysics Model with Moltres



Conclusion

ROLLO (Reactor evOLutionary aLgorithm Optimizer) Tool Development and AHTR Non-Conventional Design Optimization

- Relevance
  - The promise of additive manufacturing of reactor components free reactor design optimization from previous manufacturing constraints
  - We can now conduct nuclear reactor design optimization for non-conventional reactor geometries and fuel distributions
- Preliminary Results
  - Designed the ROLLO Python package that applies evolutionary algorithm optimization to reactor design
  - Demonstrated ROLLO's capabilities with a single objective function problem: maximize k_{eff} in the AHTR slab by varying the TRISO particle distribution
- Planned Work
  - Explore non-conventional AHTR designs with multi-objective optimizations
  - Objectives: min(fuel amount), max(heat transfer), min(power peaking factor)
  - Control parameters: TRISO distribution, total PF, coolant channel shape



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Appendix

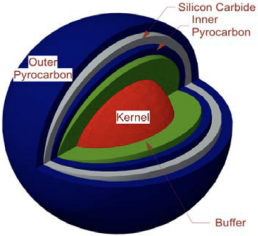

Figure 26: AHTR's TRISO particle schematic reproduced from [1].

Table 10: TRISO Fuel Dimensions.

Parameter	Size [cm]	Material model as	Density [g/cc]
Fuel Kernel (Oxycarbide) Radius	0.02135	UCO, 9% enriched	11.0
Buffer (Porous Carbon) Radius	0.03135	Carbon	1.0
Inner Pyrolytic Carbon (IPyC) Radius	0.03485	Graphite	1.8
Silicon Carbide (SiC) Layer Radius	0.03835	Silicon Carbide	3.2
Outer Pyrolytic Carbon (OPyC) Radius	0.04235	Graphite	1.8
Fuel Stripe Cubic Lattice Pitch	0.09266	Lattice matrix graphite	1.8

Appendix

- In each ROLLO simulation, each generation runs a population size number of individual OpenMC simulations
- Each OpenMC simulation takes approximately 13 minutes to run on a single BlueWaters XE node
- With approximately 600 OpenMC evaluations per ROLLO simulation, the ROLLO simulation takes about 130 BlueWaters node-hours
- The hyperparameter search ran 40 ROLLO simulations, thus using approximately 5200 node-hours.