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and cost efficiencies via

Gains in operational flexibility, safety margins,

integrated Plant Reload Optimization platform

Background: Why it is important?

2022 Cost Summary (\$/MWh)*



- Fuel takes ~17% of the total generating cost
 - Costs ~\$43M for a typical LWR fuel reload in a year

Factors affecting Fuel Cost**



- Traditional methods deciding core loading pattern and reload quantity are labor-intensive and time-consuming.
 - More than 10E+30 combinations for 17x17 PWR core

Automated simulation-based fuel reloading analysis Framework is needed.

* Nuclear Energy Institute (2023). "Nuclear Costs In Context." NEI ** International Atomic Energy Agency (2020). "Reload Design and Core Management in Operating Nuclear Power Plants." IAES-TECDOC-1898, IAEA

Plant ReLoad Optimization (PRLO) Platform: Data Flow



HCF: Hot channel factor

DBA: Design basis accident

EFPD: Effective full power day PCT: Peak cladding temperature DNBR: Departure of nucleate boiling rate HTC: Heat transfer coefficient

TH: Thermal-hydraulics **RIP: Rod internal pressure** FFRD: Fuel failure, relocation and dispersal

Case Study: Single-objective Optimization for Core Design Introduction

- Settings
 - PWR core with 157 fuel assemblies (FA)
 - Quarter-core symmetry
 - 6 FA designs \rightarrow design space = 7.1×10³²
 - 200 Population w/ 90 Iteration for GA

Fuel type ID	0	1	2	3	4	5
Enrichment (wt%)	2	2.5	2.5	3.2	3.2	Reflector
Burnable poison	None	None	16 Gd rods	None	16 Gd rods	-



- Objective
 - Maximize cycle length (cycle energy production)
- Constraints
 - F_Q (Heat flux hot channel factor) < 2.1
 - $F_{\Delta H}$ (Nuclear enthalpy rise hot channel factor) < 1.48
 - Peak critical boron concentration (CBC) <1300 pcm

Case Study: Single-objective Optimization for Core Design Demonstration



Case Study: Single-objective Optimization for Core Design Demonstration



A generic PWR reactor core is used for the demonstration

Case Study: Multi-objective Optimization for Core Design Introduction

- Settings
 - PWR core with 157 fuel assemblies (FA)
 - Quarter-core symmetry
 - 6 FA designs \rightarrow design space = 7.1×10³²
 - 100 Population w/ 50 Iteration for GA

Fuel type ID	1	2	3	4	5	6
Enrichment (wt%)	Reflector	2	2.5	2.5	3.2	3.2
Burnable poison	-	None	None	16 Gd rods	None	16 Gd rods





- Objectives
 - Maximize cycle length (cycle energy production)
 - Minimize fuel cost

- Constraints
 - F_Q (Heat flux hot channel factor) < 2.1
 - $F_{\Delta H}$ (Nuclear enthalpy rise hot channel factor) < 1.48
 - Peak critical boron concentration (CBC) <1300 pcm

NOTE: F_Q and $F_{\Delta H}$ are peaking factors used to characterize core power distribution in terms of ratios of local maximum power output to average core output.

A generic PWR reactor core is used for the demonstration

Demonstration with Multi Objective Optimal Core Patterns





383.50

520.92

2.098

1296.8

1.476

373.80

508.28

2.090

1293.9

1.466

364.10

499.45

2.092

1295.6

1.479

A generic PWR reactor core is used for the demonstration

Demonstration with Multi Objective Common Features of Optimal Core Designs

• All three core designs present the Low Leakage Loading pattern (L3P)

- Low/medium reactivity fuel at inner region to reduce the power peaking at core center
- High reactivity fuel at outer region to balance the power
- Use of BP to suppress the excess reactivity
- Low reactivity fuel at core boundary to reduce the leakage / increase the neutron economy



Conclusion & Future Work

- Presented the PRLO framework, aimed at Al-driven reactor core design for addressing real-world challenges.
- Demonstrated constrained multi-objective core design optimization problem for a 17 × 17 PWR core to minimize fuel cost and maximize fuel cycle length.
- Future works include...
 - Conducting a full-scale demonstration of a PWR core design with multi-cycle problem incorporating safety analysis.
 - Enhancing multi-objective optimization capabilities (e.g., adaptive mutation and crossover)

Completed Works (~FY24)



- Demonstration of Genetic Algorithm-based optimization framework with single/multi-objective(s).
- Design of optimized reactor core which considers system safety analysis and fuel performance, thus multiphysics methodology.
- Reports are available at: https://www.osti.gov/





Genetic Algorithm

- GA mimics natural selection and evolution
 - No need of gradient calculation
 - Suits non-linear and non-convex problems
 - Constrained and unconstrained
 - Continuous, discrete, or mixed variables
- GA explores group of solutions at each iteration
 - Starts with initial list of solutions (neutronics, thermal-hydraulics, etc.)
 - Evaluates and determines potential solutions
 - Randomly proposes new solutions, then selects best solution (cross-over, mutation, and survivor selection operations).



Evolutionary Operators of GAs

- Parent selectors:
 - Roulette Wheel
 - Tournament Selection
 - Rank Selection

<GAparams>

<populationSize>10</populationSize>

<parentSelection</pre>>rouletteWheel</parentSelection</pre>



Individual	Fitness
P1	5
P2	8.2
P3	1.4
P4	0.98
P5	2
P6	2.3

Evolutionary Operators of GAs

- Crossovers:
 - One Point
 - Two points
 - Uniform



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Evolutionary Operators of GAs

- Mutators:
 - Swap Mutation
 - Scramble Mutation
 - Bit Flip Mutation
 - Inversion Mutation





NSGA-II for Multi-Objective Problem Overview

- NSGA-II is...
 - Multi-objective, fast non-dominated sorting elite GA
- Why NSGA-II?
 - Lower computational complexity than NSGA-I
 - Population diversity is guaranteed.
 - One of the multi-objective evolutionary computation benchmark

A multi-objective optimization problem can be written as

Minimize (or maximize) $(f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_M(\mathbf{x}))^T$ Subject to $g_j(\mathbf{x}) \ge (\text{or } \le) 0$ $h_k(\mathbf{x}) = 0$ $x_i^{(L)} \le x_i \le x_i^{(U)}$

- $f_m(x)$ is *m*-th objective, where m = 1, 2, ..., M.
- $g_j(x)$ is *j*-th inequality constraint, where j = 1, 2, ..., J
- $h_k(x)$ is k-th equality constraint, where k = 1, 2, ..., K
 - $\mathbf{x} = (x_1, x_2, ..., x_n)^T$ is a n-dimensional vector
- $x_i^{(L)}$ and $x_i^{(U)}$ are the lower and upper bounds on *i*-th variable



NSGA-II for Multi-Objective Problem Elitism

- Keep the best chromosomes from parent and offspring population
- Elitism does not allow an already found optimal solutions to be deleted.



NSGA-II for Multi-Objective Problem Dominance Depth Method

- Assign rank to each chromosome using the dominance depth
- Non-dominated points belong to first rank.
- The non-dominated solutions from remainder are in second rank, and so on.



NSGA-II for Multi-Objective Problem Niching for the first rank



- Niching gives preference to chromosomes that are not crowded.
- Crowding distance measures crowdedness of a chromosome w.r.t. its neighbors lying on the same front.
 - Crowding distance = a + b
 - a and b are normalized distances.
- Chromosomes from the first rank are selected based on niching.

Case Study: Multi-objective Optimization for Core Design Feasible Region and Pareto Frontier

