INL/MIS-24-77706-Revision-0

Gains in operational flexibility, safety margins, and cost efficiencies via integrated Plant Reload Optimization platform

May 2024

Changing the World's Energy Future

Junyung Kim, Svetlana Lawrence, Mohammad Gamal M Mostafa Abdo, Juan C. Luque-Gutierrez, Nicholas Rollins, Jason Hou, Boyan Ivanov, Adam Donell, Seth Spooner

Idaho National Laboratory

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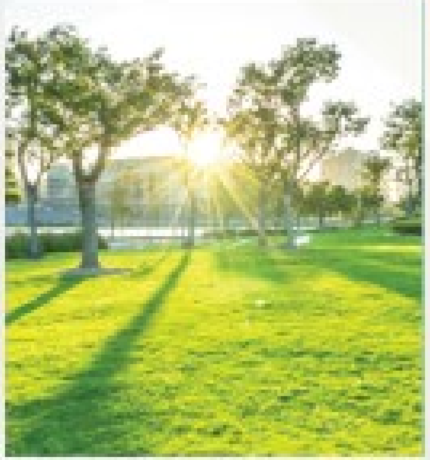
Gains in operational flexibility, safety margins, and cost efficiencies via integrated Plant Reload Optimization platform

Constellation: America's Leading Clean Energy Company

#1
Producer of carbon free energy in the US

32,400 MW
Of capacity consisting of nuclear, wind, solar, natural gas and hydro, enough to power 20 million homes.



10%
Of the nation's carbon-free energy

~12k
Employees nationwide

215 TWh
Of power served to commercial customers

#1
In market share for C&I customers

3/4
Of Fortune 100 companies count on us for their energy needs

~64k
Employee volunteer hours in 2021

Nuclear Facilities

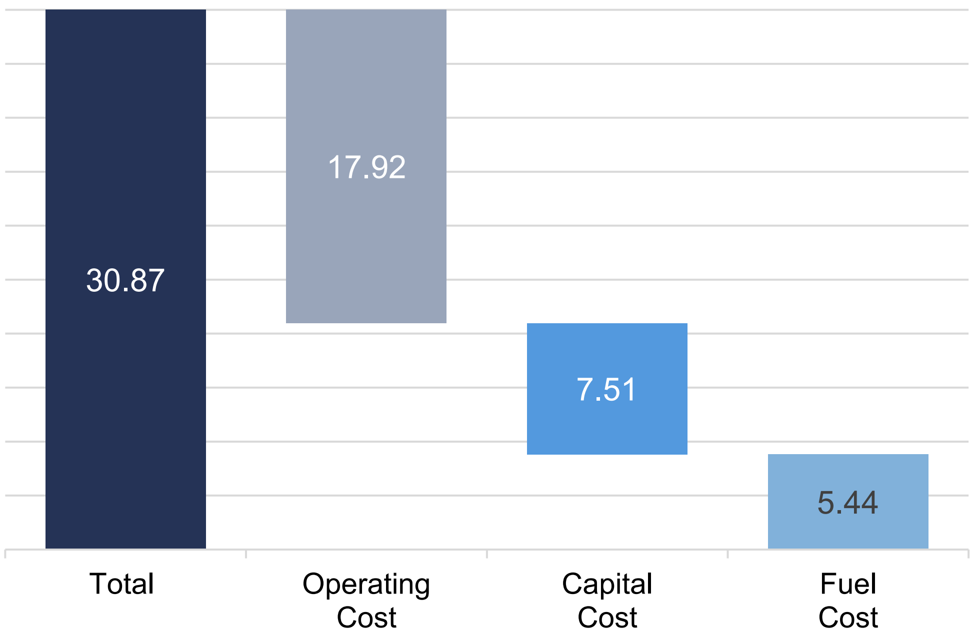
- Constellation owns & operates the largest fleet of nuclear plants in America, with 21 reactors in 4 states, serving approximately 15 million homes.

Locations & number of sites and operational units by state

1. Illinois: 6 sites with 11 units
2. New York: 3 sites with 4 units
3. Pennsylvania: 2 sites with 4 units
4. Maryland: 1 site with 2 units

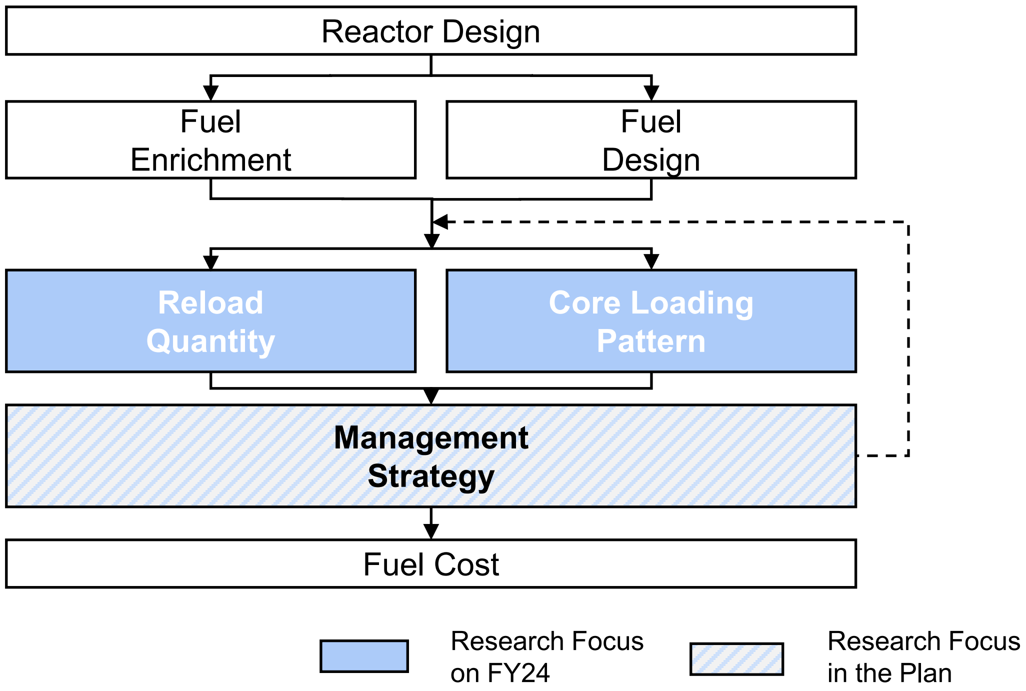
Background: Why it is important?

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**



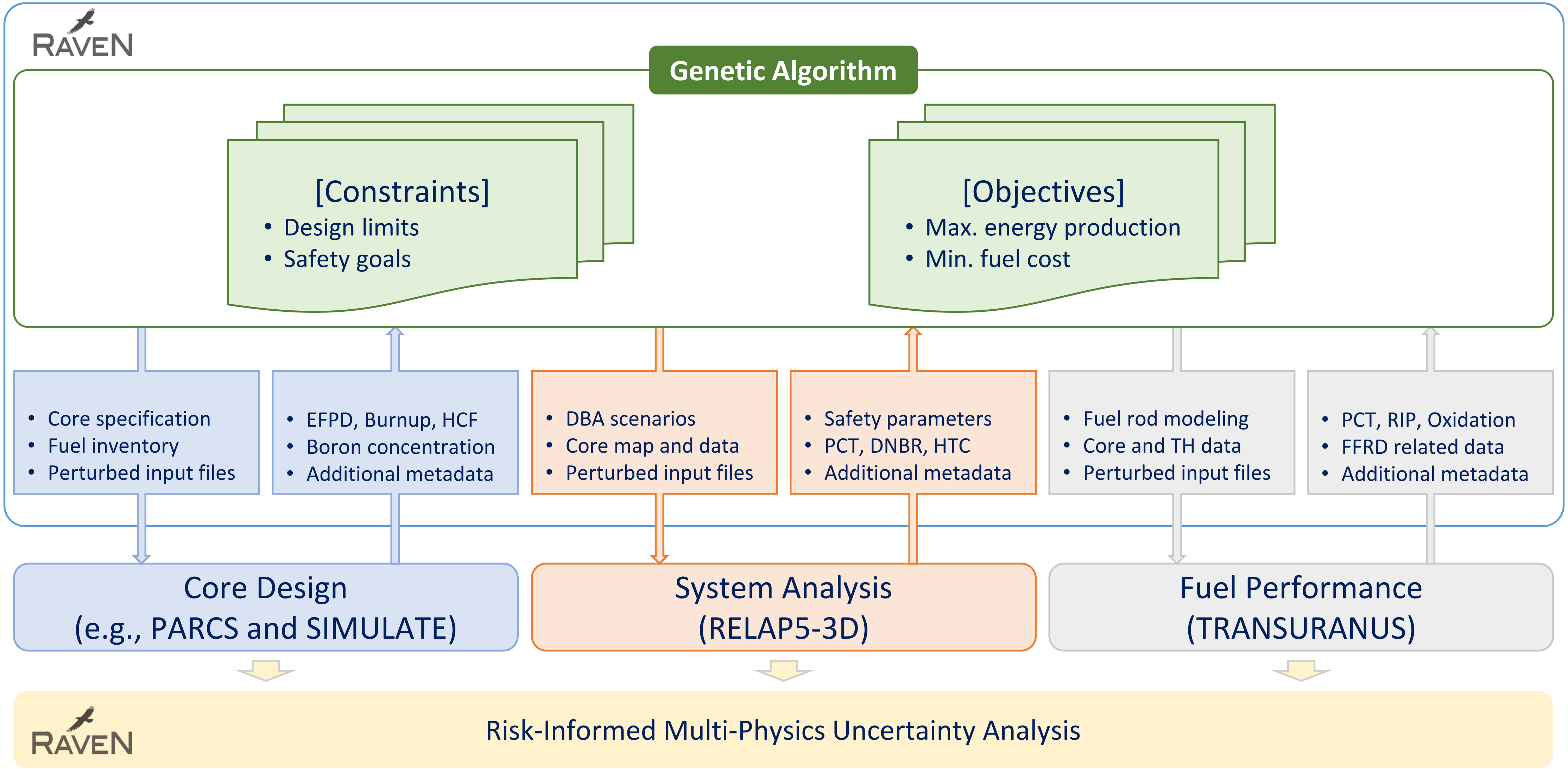
- **Traditional methods deciding core loading pattern and reload quantity are labor-intensive and time-consuming.**
  - More than 10E+30 combinations for 17x17 PWR core

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



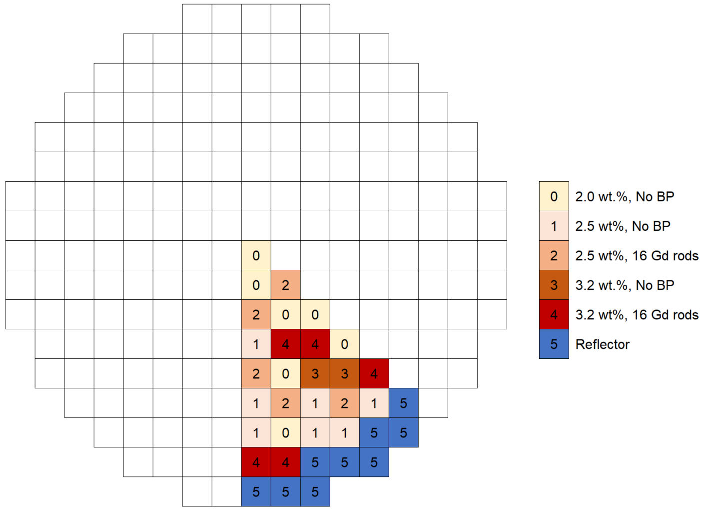
EFPD: Effective full power day
HCF: Hot channel factor
DBA: Design basis accident

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 → design space = 7.1×10^{32}
  - 200 Population w/ 90 Iteration for GA



Randomly generated 1/8 PWR Core

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

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.

Case Study: Single-objective Optimization for Core Design Demonstration

Case Study: Single-objective Optimization for Core Design Demonstration

Initial Fuel Loading Pattern

						5	5	5	5	5						
				5	5	5	4	4	4	5	5	5				
			5	5	1	1	0	1	0	1	1	5	5			
		5	5	1	2	1	2	1	2	1	2	1	5	5		
	5	5	1	4	3	3	0	2	0	3	3	4	1	5	5	
	5	1	2	3	0	4	4	1	4	4	0	3	2	1	5	
5	5	1	1	3	4	0	0	2	0	0	4	3	1	1	5	5
5	4	0	2	0	4	0	2	0	2	0	4	0	2	0	4	5
5	4	1	1	2	1	2	0	0	0	2	1	2	1	1	4	5
5	4	0	2	0	4	0	2	0	2	0	4	0	2	0	4	5
5	5	1	1	3	4	0	0	2	0	0	4	3	1	1	5	5
	5	1	2	3	0	4	4	1	4	4	0	3	2	1	5	
	5	5	1	4	3	3	0	2	0	3	3	4	1	5	5	
		5	5	1	2	1	2	1	2	1	2	1	5	5		
			5	5	1	1	0	1	0	1	1	5	5			
				5	5	5	4	4	4	5	5	5				
						5	5	5	5	5						

Pin_Peaking Factor	3.121	x
Boron Concentration	1492	x
FΔH	2.317	x

Effective Full Power Day (EFPD)	412.6

Optimized Fuel Loading Pattern

						5	5	5	5	5						
				5	5	5	2	2	2	5	5	5				
			5	5	2	4	4	0	4	4	2	5	5			
		5	5	4	2	4	1	1	1	4	2	4	5	5		
	5	5	4	4	1	0	0	3	0	0	1	4	4	5	5	
	5	2	2	1	0	1	0	1	0	1	0	1	2	2	5	
5	5	4	4	0	1	0	3	0	3	0	1	0	4	4	5	5
5	2	4	1	0	0	3	0	0	0	3	0	0	1	4	2	5
5	2	0	1	3	1	0	0	1	0	0	1	3	1	0	2	5
5	2	4	1	0	0	3	0	0	0	3	0	0	1	4	2	5
5	5	4	4	0	1	0	3	0	3	0	1	0	4	4	5	5
	5	2	2	1	0	1	0	1	0	1	0	1	2	2	5	
	5	5	4	4	1	0	0	3	0	0	1	4	4	5	5	
		5	5	4	2	4	1	1	1	4	2	4	5	5		
			5	5	2	4	4	0	4	4	2	5	5			
				5	5	5	2	2	2	5	5	5				
						5	5	5	5	5						

Pin_Peaking Factor	2.075	o
Boron Concentration	1297.6	o
FΔH	1.454	o

Effective Full Power Day (EFPD)	392.7

0	2.0 wt.%, No BP
1	2.5 wt%, No BP
2	2.5 wt%, 16 Gd rods
3	3.2 wt.%, No BP
4	3.2 wt%, 16 Gd rods
5	Reflector

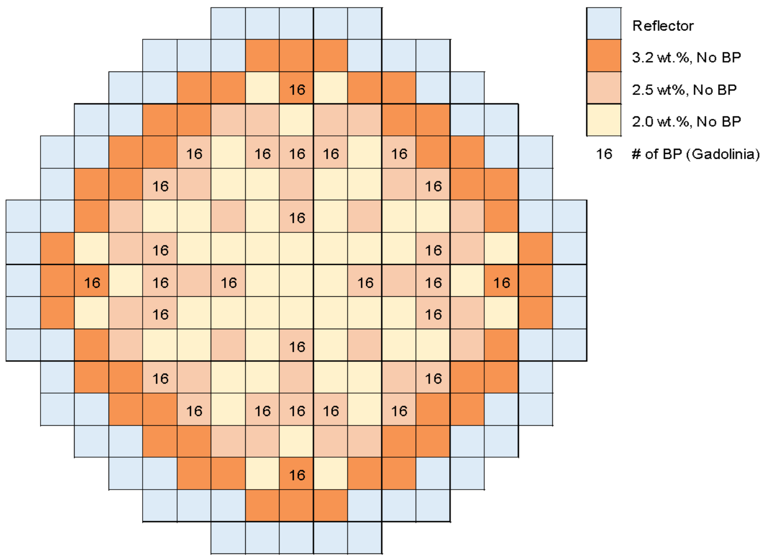
A generic PWR reactor core is used for the demonstration

Case Study: Multi-objective Optimization for Core Design Introduction

- Settings
  - PWR core with 157 fuel assemblies (FA)
  - Quarter-core symmetry
  - 6 FA designs → design space = 7.1×10^{32}
  - 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

Randomly generated PWR Core



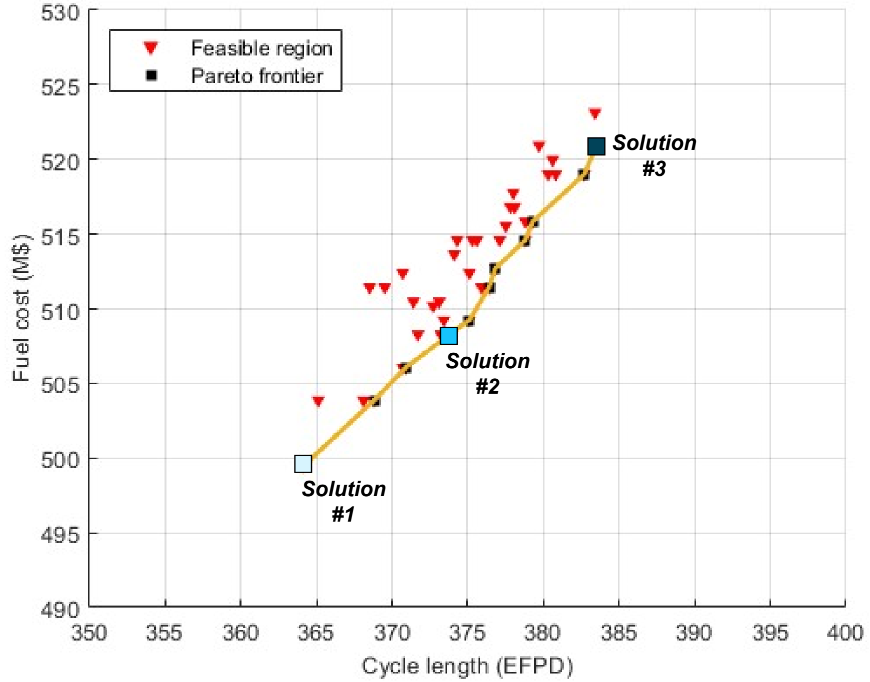
- Objectives
  - Maximize cycle length (cycle energy production)
  - Minimize fuel cost

- 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.

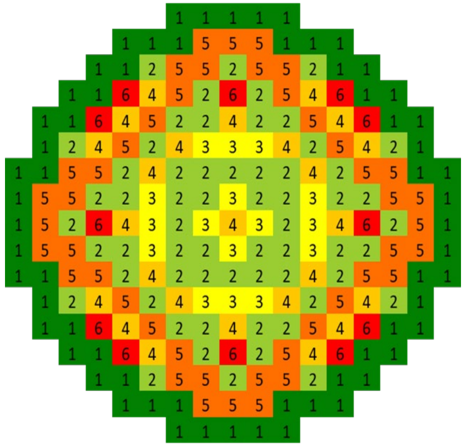
A generic PWR reactor core is used for the demonstration

Demonstration with Multi Objective Optimal Core Patterns



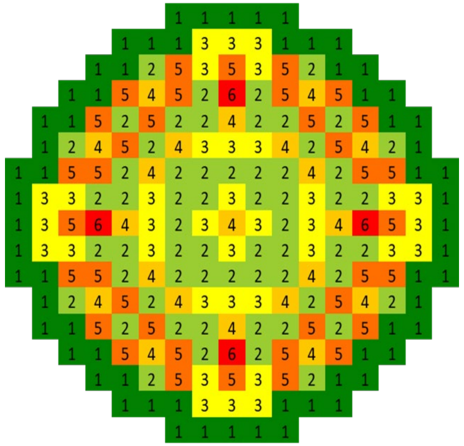
A generic PWR reactor core is used for the demonstration

Solution #3



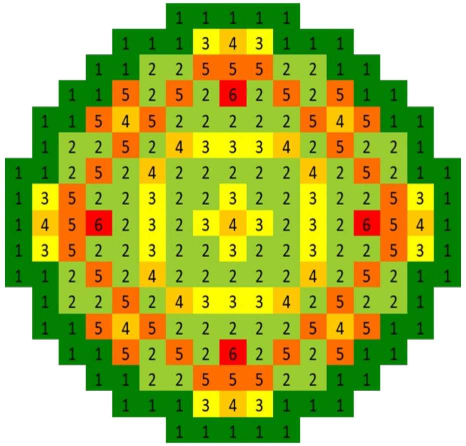
Cycle length (EFPD)	383.50
Fuel cost (M$)	520.92
F_Q	2.098
CBC (ppm)	1296.8
$F_{\Delta H}$	1.476

Solution #2



Cycle length (EFPD)	373.80
Fuel cost (M$)	508.28
F_Q	2.090
CBC (ppm)	1293.9
$F_{\Delta H}$	1.466

Solution #1

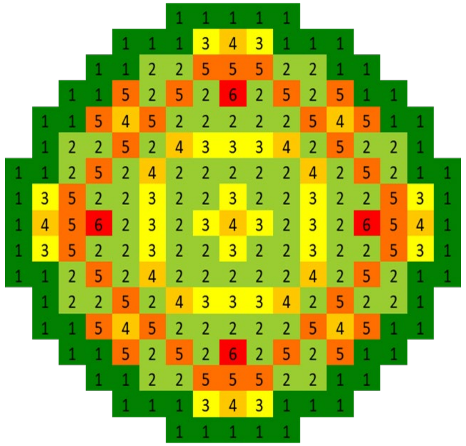


Cycle length (EFPD)	364.10
Fuel cost (M$)	499.45
F_Q	2.092
CBC (ppm)	1295.6
$F_{\Delta H}$	1.479

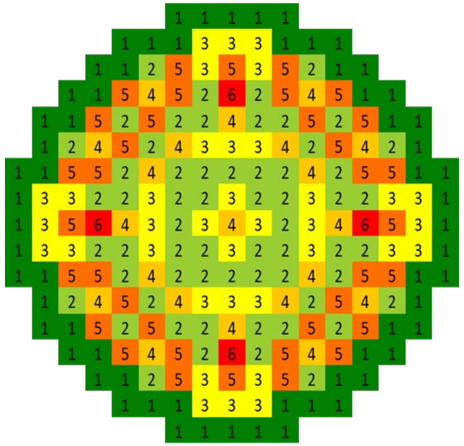
Demonstration with Multi Objective
Common Features of Optimal Core Designs

- **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

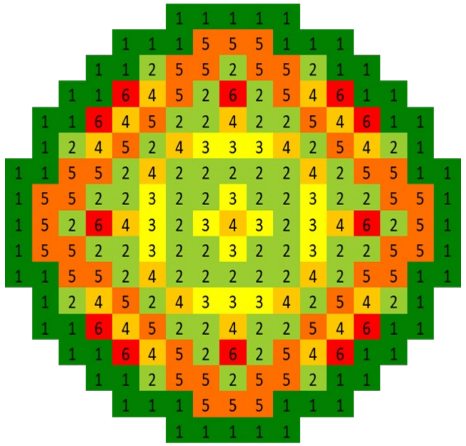
Solution #1



Solution #2



Solution #3

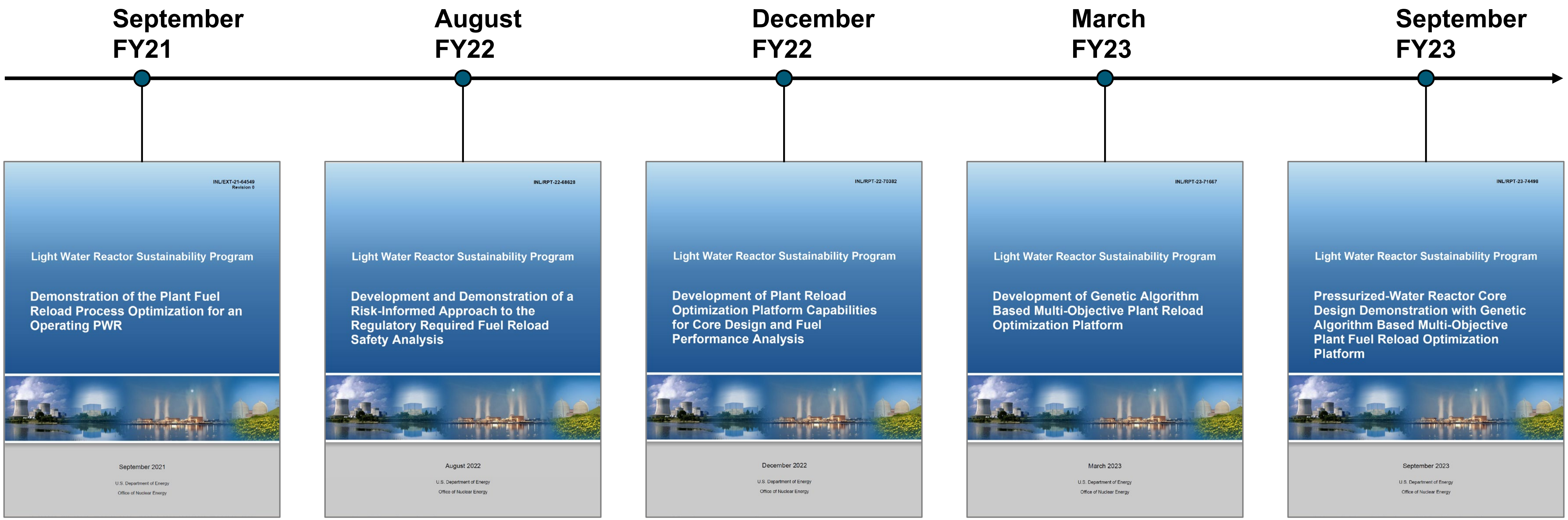


A generic PWR reactor core is used for the demonstration

Conclusion & Future Work

- **Presented the PRLO framework, aimed at AI-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 multi-physics methodology.**
- **Reports are available at: https://www.osti.gov/**

LWRS

LIGHT WATER REACTOR SUSTAINABILITY

INL Idaho National Laboratory

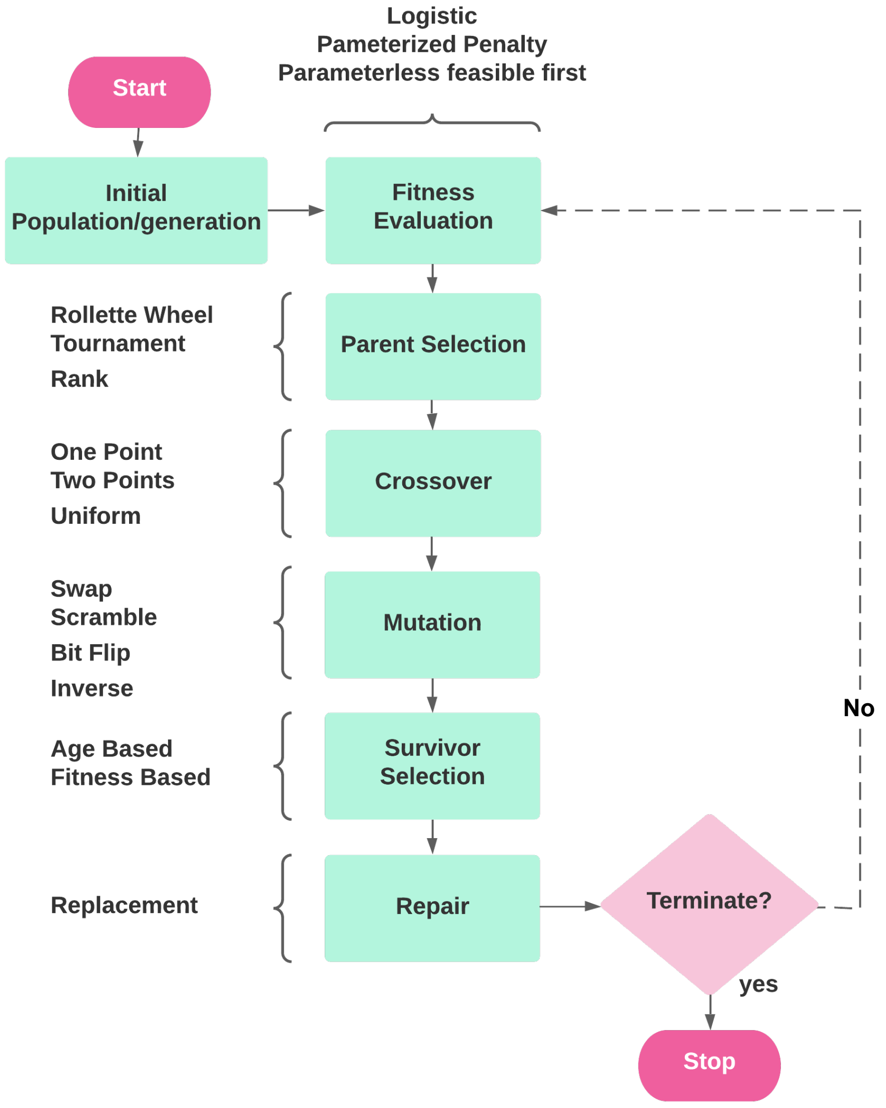
NC STATE UNIVERSITY

Constellation

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

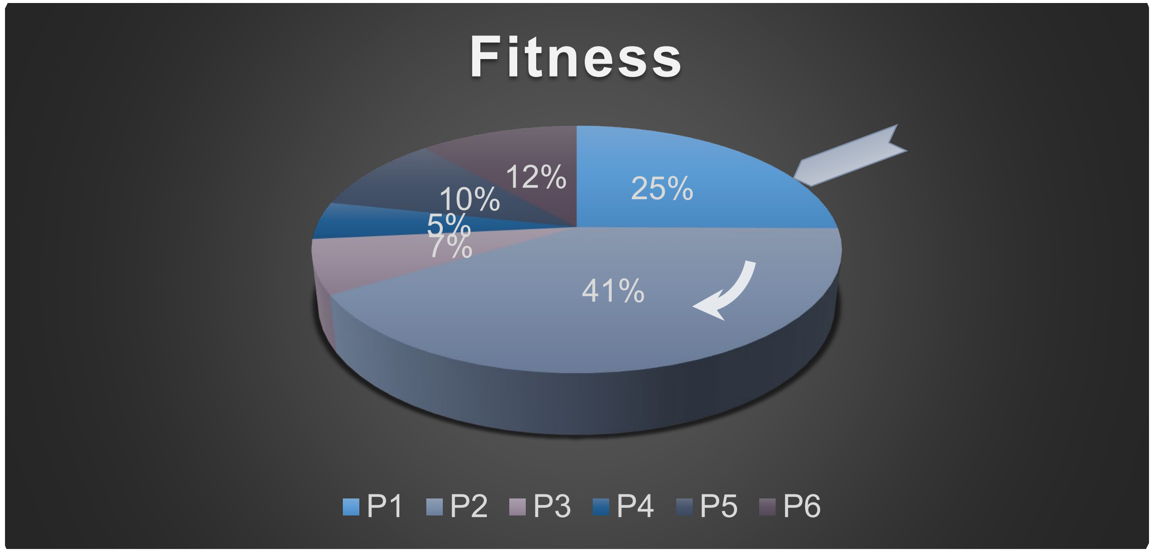
- GA explores group of solutions at each iteration
  - Starts with initial list of solutions (neutronics, thermal-hydraulics, etc.)
  - Evaluates and determines potential solutions
  - Randomly proposes new solutions, then selects best solution (cross-over, mutation, and survivor selection operations).



Evolutionary Operators of GAs

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

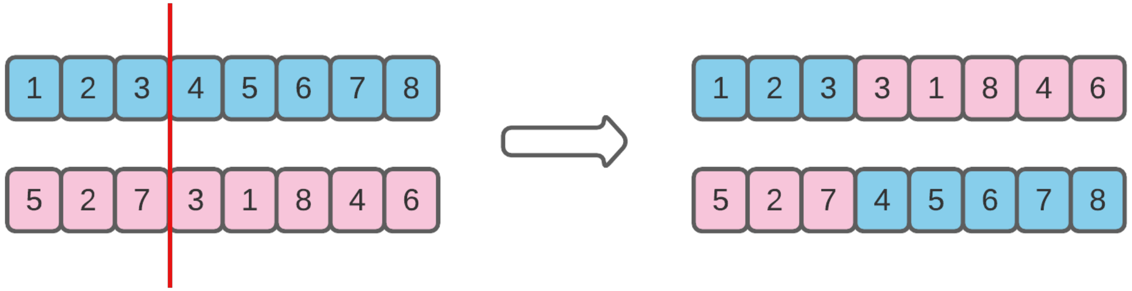
```xml
<GAparams>
  <populationSize>10</populationSize>
  <parentSelection>rouletteWheel</parentSelection>
```



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




```xml
<reproduction>
    <crossover type="onePointCrossover">
        <crossoverProb>0.8</crossoverProb>
    </crossover>        You, 19 months ago •
    <mutation type="scrambleMutator">
        <mutationProb>0.9</mutationProb>
    </mutation>
</reproduction>
```

Evolutionary Operators of GAs

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


```xml
<reproduction>
  <crossover type="onePointCrossover">
    <crossoverProb>0.8</crossoverProb>
  </crossover>
  <mutation type="scrambleMutator">
    <mutationProb>0.9</mutationProb>
  </mutation>        You, 19 months ago •
</reproduction>
```

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

$$\textbf{Minimize (or maximize) } (f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \dots, f_M(\boldsymbol{x}))^T$$

Subject to

$$g_j(\boldsymbol{x}) \geq (\text{or } \leq) \ 0$$

$$h_k(\boldsymbol{x}) = 0$$

$$x_i^{(L)} \leq x_i \leq x_i^{(U)}$$

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

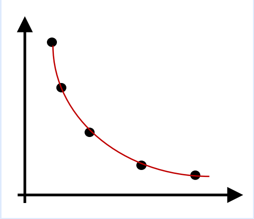
Multi-objective optimization problem subject to constraints

↓

Multi-objective optimization technique

↓

Multiple optimal solutions

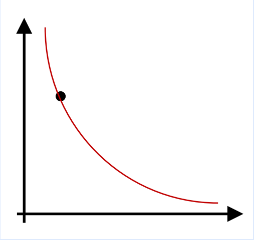


↓

Higher-level information (or operator's decision)

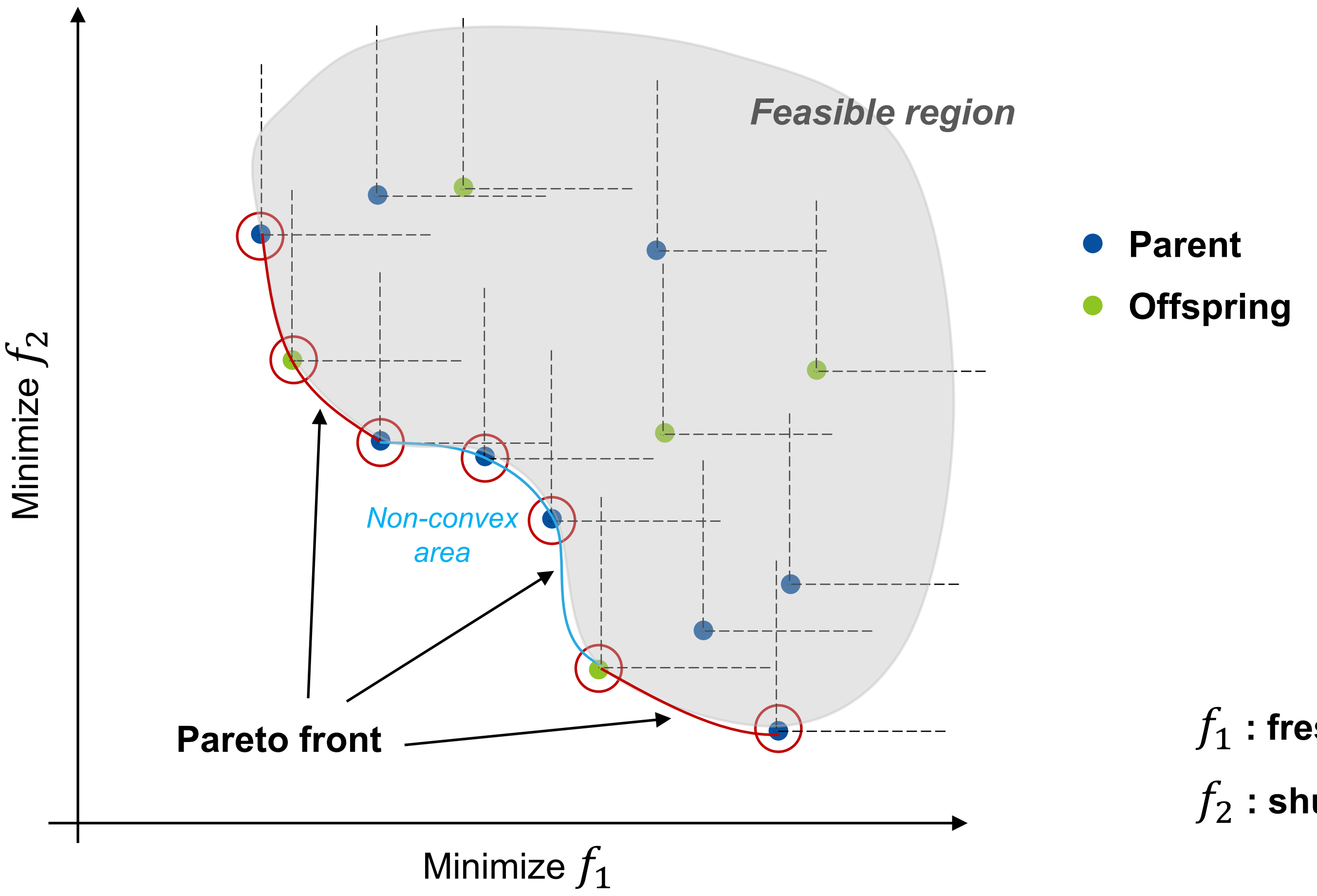
↓

One optimal solution



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.**

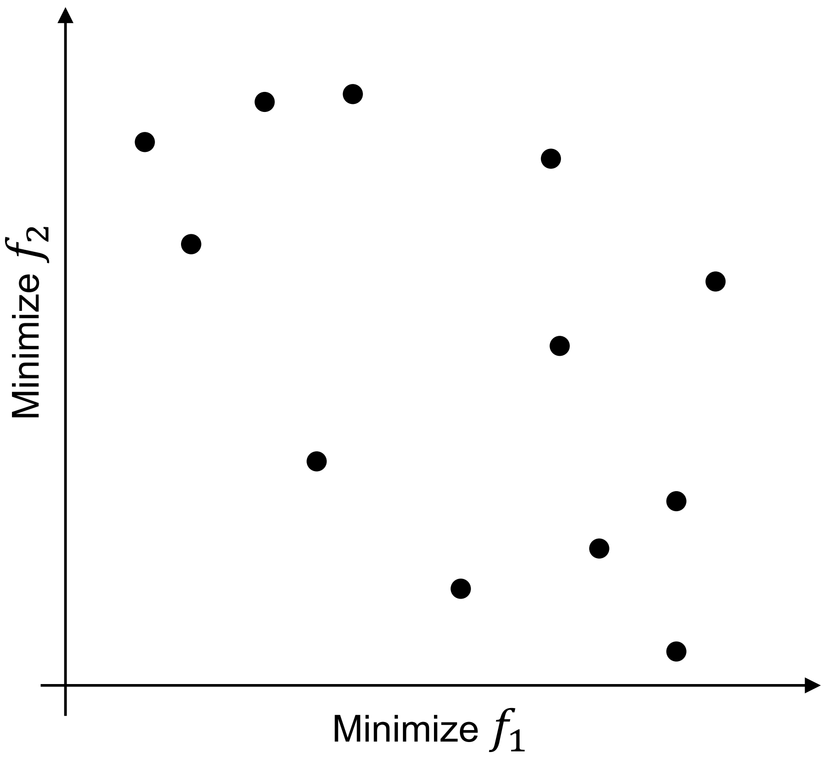


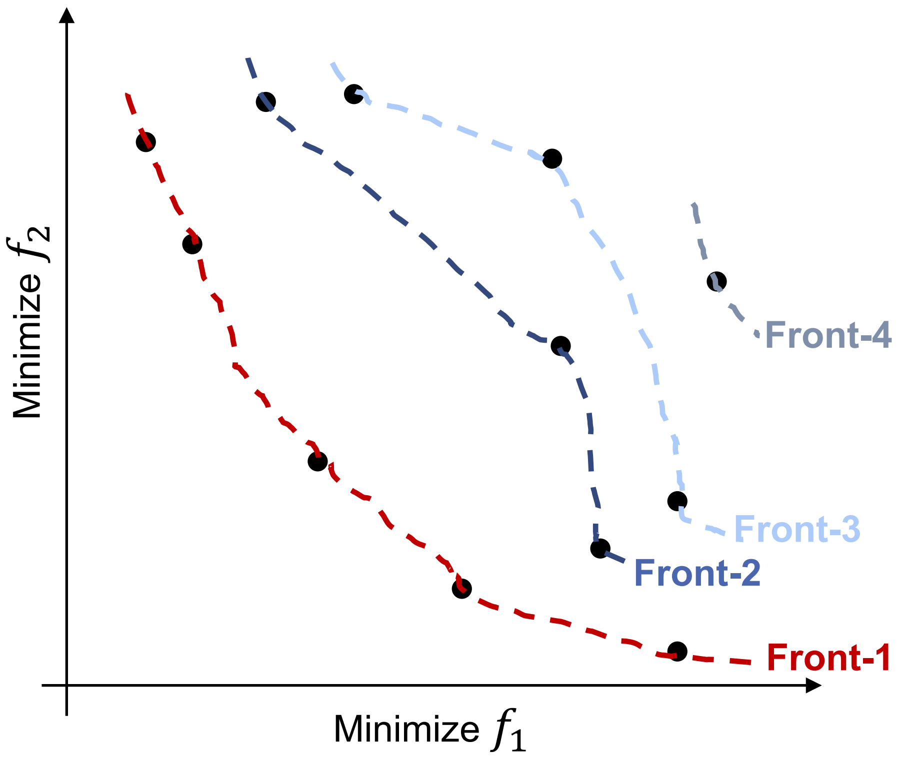
f_1 **: fresh fuel**

f_2 **: shutdown margin**

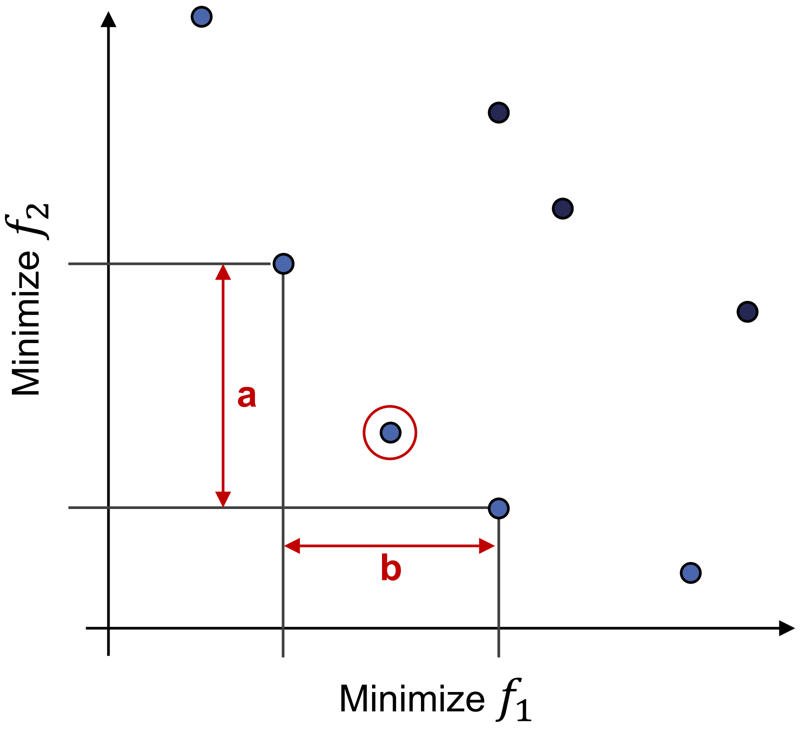
NSGA-II for Multi-Objective Problem
Dominance Depth Method

- **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.**



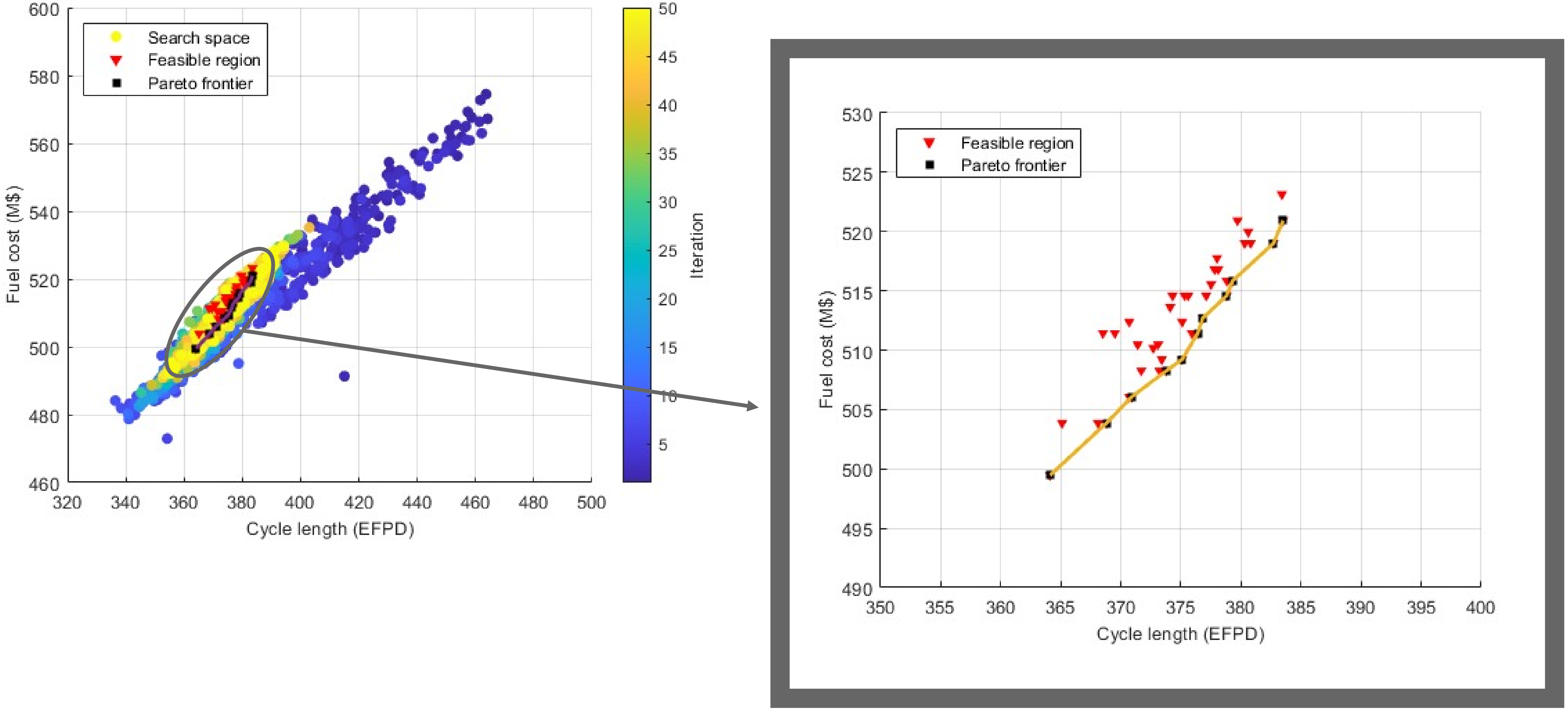


NSGA-II for Multi-Objective Problem
Niching for the first rank



- **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



NOTE: Feasible region: Search space region where all constraints are complied; Pareto frontier: Set of optimal solutions