Numerical Experiments for Testing Demand-Driven Deployment Algorithms

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Outline

1) Background
    - Gap in capability of current fuel cycle simulators
    - Agent based fuel cycle simulator: Cyclus
2) Motivation
    - Demand-driven deployment algorithms
    - Impact of numerical experiments
3) Prediction Algorithms
    - Types of prediction algorithms
    - Non-optimizing method
4) Numerical Experiments
    - Numerical tests for non-optimizing method

Current fuel cycle simulators

Gap in capability: User must define when facilities are deployed

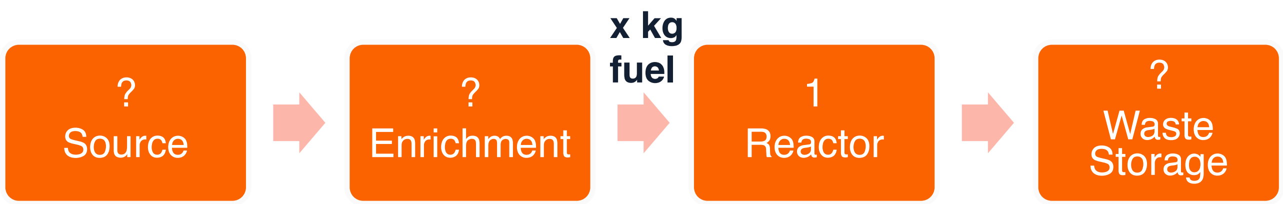


Figure 1: User defined Deployment Scheme

Bridging the gap: Developing prediction algorithms for Cyclus [2]

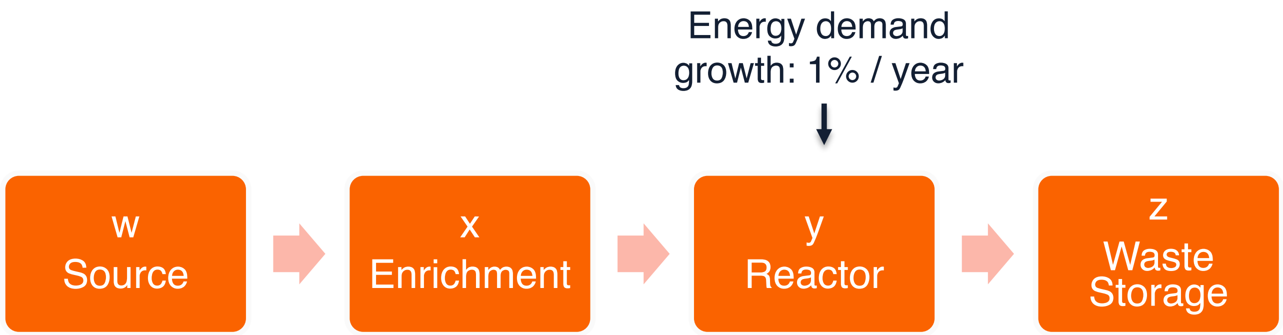


Figure 2: Demand Driven Deployment Scheme

CYCLUS

- Agent-based framework [2]
- Compatible with plug-in libraries
- Gives users ability to customize agents
- Agent types: facilities, institutions and regions
- Discrete time steps

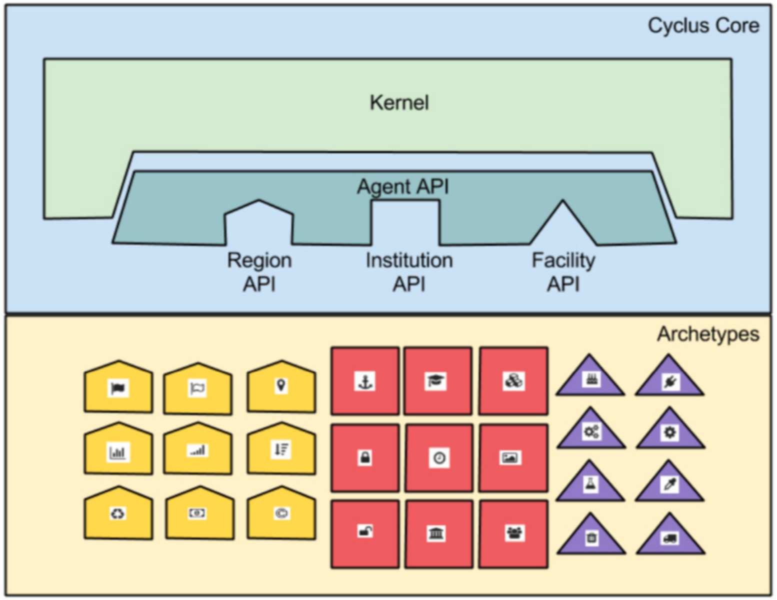


Figure 3: Cyclus has a modular architecture [3]

Demand-Driven Deployment Algorithms

- Objective function
- Examples:

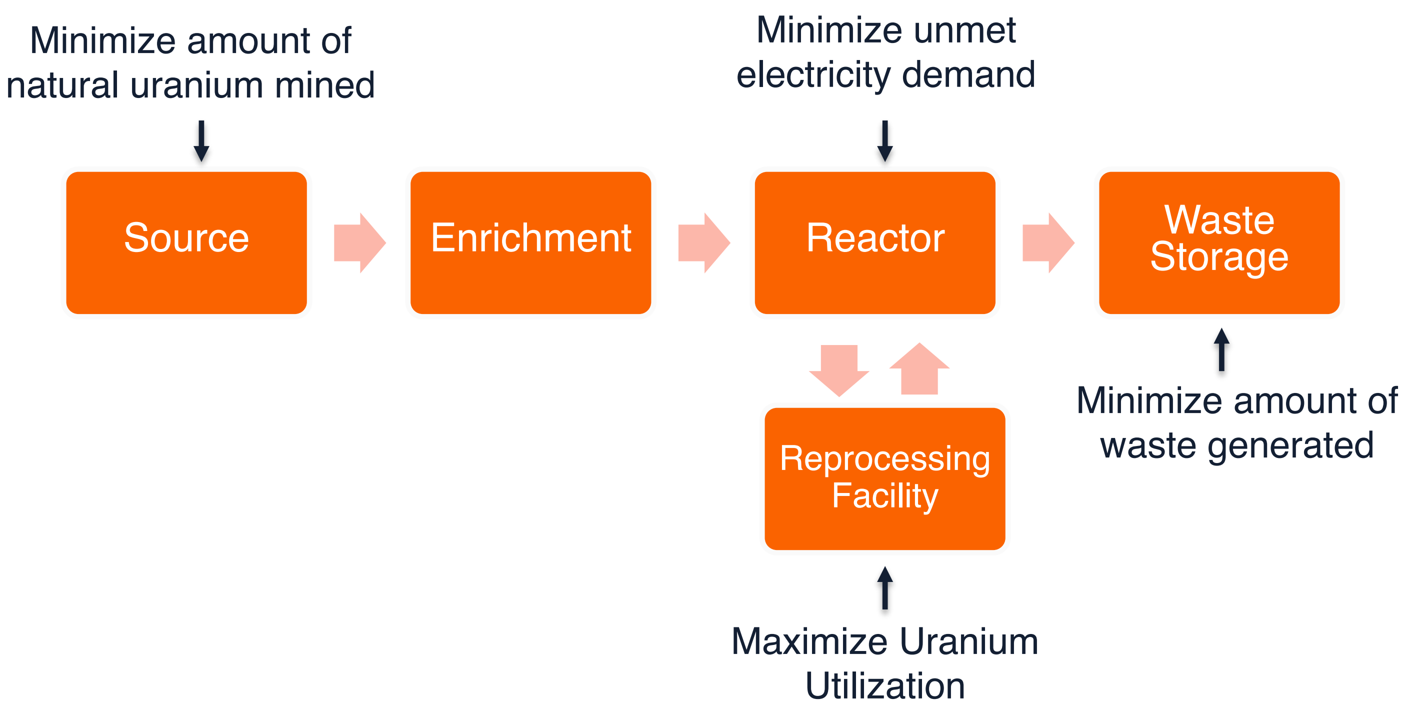


Figure 5: Demand Driven Deployment Scheme with objective functions defined

Numerical Experiments / Tests

- Verification and maintenance of code is crucial for reliability of algorithms [8]
- Best practice: writing tests

Objective of this presentation

Description of tests for the non-optimizing type prediction algorithm

Types of Prediction Algorithms

1) Non-optimizing algorithm
2) Deterministic optimization algorithm
3) Stochastic optimization algorithm [7]

Each method

- Create a supply chain
- Demand for each commodity is evaluated
- Algorithm will make a prediction about future demand
- Deploy/decommission facilities

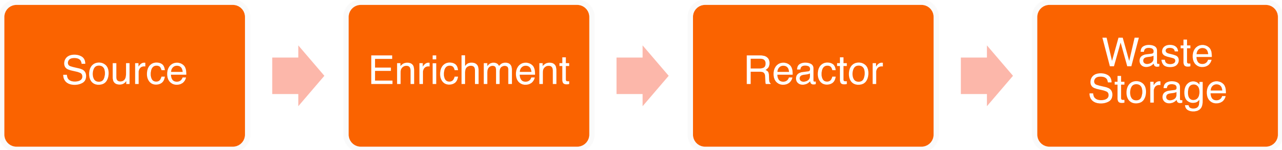


Figure 6: Prediction Algorithm creates a supply chain

Non-Optimizing Method

- Most basic prediction algorithm
- Predicts future deployment of facilities based on historical data
  - At each time step, the difference in supply and demand is calculated
  - If the difference is larger than the capacity of 1 facility, more facilities will be deployed/decommissioned
- Autoregressive Model
  - A model that is dependent only on previous outputs of the system [7]

Tests for Variation of Input Parameters

User-defined Input Parameters

1) Initial demand value
2) Number of initial facilities already present (initial supply)
3) Growth rate of initial demand
   - Growth Rate:

$$D_f(timestep) = D_i(1+g)^{(\frac{timestep}{12})}$$

Objective of varying input parameters

Ensure algorithm will deploy/decommission facilities correctly for different test scenarios

Test Scenarios & Analytical Solutions

1 Source Facility → Output: 1kg **Fuel**

Table 1: Test Scenario Parameters

Test Scenario Parameters	Value	Units
Duration	15	timesteps
Timestep	1	month
Start Month	1	month
Start Year	2000	year

Table 2a: Test A1 Scenario Input Parameters

Source Parameter	Value	Units
Initial demand	1	kg
Initial facilities	0	#
Growth Rate	0	

Table 2b: Test A1 Analytical Solution

Time Step	No. of Source Facilities Deployed
1	1
2 to 15	0

Table 3a: Test A2 Scenario Input Parameters

Source Parameter	Value	Units
Initial demand	2	kg
Initial facilities	1	#
Growth Rate	0	

Table 3b: Test A2 Analytical Solution

Time Step	No. of Source Facilities Deployed
1	1
2 to 15	0

Table 4a: Test A3 Scenario Input Parameters

Source Parameter	Value	Units
Initial demand	1	kg
Initial facilities	0	#
Growth Rate	1	

Table 4b: Test A3 Analytical Solution

Time Step	No. of Source Facilities Deployed
1	2
2 to 12	0
13	1
14 to 15	0

Tests Scenarios & Analytical Solutions

1 Source Facility → Output: 1kg **Fuel** → 1 Reactor Facility → Output: 1MW **Power**

Table 5a: Test A4 Scenario Input Parameters

Source Parameter	Value	Units
Initial demand	-	kg
Initial facilities	-	#
Growth Rate	-	
Reactor Parameter	**Value**	**Units**
Initial demand	1	MW
Initial facilities	0	#
Growth Rate	0	

Table 5b: Test A4 Analytical Solution

Time Step	No. of Source Facilities Deployed	No. of Reactor Facilities Deployed
1	1	1
2 to 15	0	0

Table 6a: Test A5 Scenario Input Parameters

Source Parameter	Value	Units
Initial demand	-	kg
Initial facilities	-	#
Growth Rate	-	
Reactor Parameter	**Value**	**Units**
Initial demand	2	MW
Initial facilities	1	#
Growth Rate	0	

Table 6b: Test A5 Analytical Solution

Time Step	No. of Source Facilities Deployed	No. of Reactor Facilities Deployed
1	1	1
2 to 15	0	0

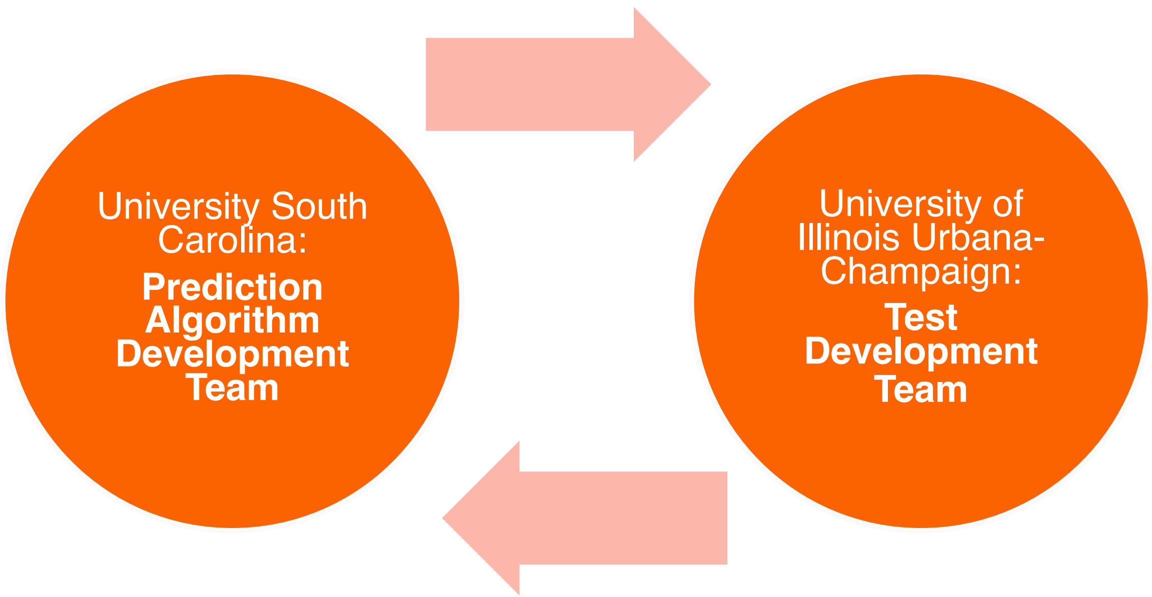
Challenges

Downsides of agent-based fuel cycle simulator

- Difficulties in implementation of generality in code

Iterative Feedback

- Striving for targeted development of prediction algorithms



Conclusion

- **Demand driven deployment algorithms** are important to meet objective functions at different phases of the fuel cycle
- **Numerical experiments** are being implemented to test the algorithms to ensure the reliability of the code
- **Challenges** of developing prediction algorithms for an agent based nuclear fuel cycle simulator due to the goal for their use in a general supply chains

Next Steps

- Idaho National Lab conducted nuclear fuel cycle evaluation and screening report and reported 40 promising fuel cycles
- Use Prediction Algorithms to evaluate the transition from current fuel cycle to the promising fuel cycle. To get information about:
  - Resource demand
  - Facility deployment and decommissioning
  - Time span

Acknowledgements

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[4]: A.M.SCOPATZ and K.D.HUFF, "Technical Narrative for Demand-Driven Cycamore Archetypes," Technical Report, University of South Carolina and University of Illinois at Urbana-Champaign (2016).

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Thank You

Any Questions?

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Source, Reactor and Sink Parameters

Source Parameters	**Value**	**Units**
Throughput	1	kg
Output Commodity	fuel	kg
Reactor Parameters	**Value**	**Units**
Cycle Time	1	timesteps
Refuel Time	0	timesteps
Lifetime	1	timesteps
Power Capacity	1	MWe
Assembly Size	1	kg
# assemblies per core	1	
# assemblies per batch	1	
Input Commodity	fuel	kg
Output Commodity	power	MW
Sink Parameters	**Value**	**Units**
Throughput	1	kg
Input Commodity	spent uox	kg

Deterministic & Stochastic Optimization Method

- Deterministic Optimization
  - Uses known shutdown times and power produced per facility to determine global solutions
- Stochastic Optimization
  - Stochastic prediction with standard deviations derived from recent historical data to generate high, mean and low curves into the future
  - Runs sub-simulations into the future to attempt to minimize the difference in produced quantity to demand [4]