

Demand Driven Cycamore Archetypes

FY16 NEUP Award Summary

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Gwendolyn Chee, Roberto Fairhurst, Robert Flanagan, Jin Whan Bae,
Anthony Scopatz, Travis Knight

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ILLINOIS

Outline



① Overview

Motivation
Objectives

② Accomplishments

GIS Capability
Challenge Problem
d3ploy
Comparison of Prediction Methods

③ Conclusion

Conclusion
Auxilliary Activities

Overview



Title: Demand-Driven Cycamore Archetypes

PI: Anthony Scopatz, University of South Carolina¹

Co-PI: Kathryn Huff, University of Illinois at Urbana-Champaign

Start: October, 2016

End: October, 2017

Objectives: Develop an in situ demand driven development schedule calculation through non-optimizing, deterministic-optimizing, and stochastic-optimizing algorithms as Cyclus archetypes. Demonstrate these new archetypes in program-supporting fuel cycle scenarios.

¹Anthony departed academia in year 2 of the project. The PIship was transferred to Travis Knight at USC

Quick Statistics



Publications Affiliated with this Work

Journal Articles 3 (2 upcoming)

Full Conference Papers 3 (2 upcoming)

Conference Summaries 7

Technical Reports 2 (1 upcoming)

Theses 1MS (2 upcoming)

Students Supported

The funding supported graduate students and occasional undergraduates at UIUC. **Jin Whan Bae** received his MS and is now at ORNL pursuing Cyclus usability. **Gwendolyn Chee** is writing an MS thesis related to this work and related work conducted at ANL with Bo Feng. Undergraduate **Louis Kissinger** is a baccalaureate researcher this year in MCS at ANL. Others include **Roberto Fairhurst**, **Gyu Tae Park**, **Snehal Chandan**, and **Aditya Bhosale**.



Motivation

Main Objective

To improve usability of Cyclus for transition scenarios.

Main Challenge

Deploying reactors to meet power demand is trivial, and existed in the earliest versions of Cyclus. **Automated, predictive deployment and decommissioning of other facilities is more complex.** These include mining, milling, enrichment, fuel fabrication, reprocessing, and others.

For example, a balanced closed fuel cycle may require ensuring that there is enough fast reactor fuel for their operation and may drive deployment of a fleet of light water reactors.



Quick Statistics

Top Submitters (Issues & PRs)

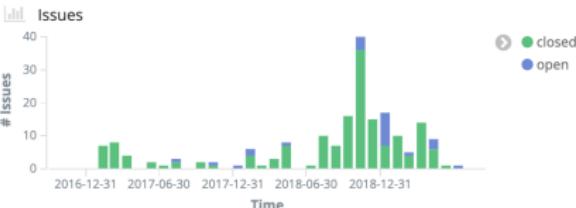
Avatar $\diamond Q$ Name $\diamond Q$ Profile $\diamond Q$



gwenchee

[gwenchee](#)

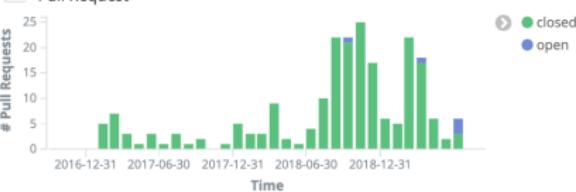
Issues



Jin Whan Bae

[jbae11](#)

Pull Request



Export: [Raw](#) [Formatted](#)

Top Authors

Name $\diamond Q$ Commits \diamond

Jin Whan Bae 1,497

gwenchee 762

gyutaepark 494

Katy Huff 71

FlanFlanagan 54

Commits



Added Vs Removed Lines



Figure 1: GitHub issues associated directly with this work.

Quick Statistics

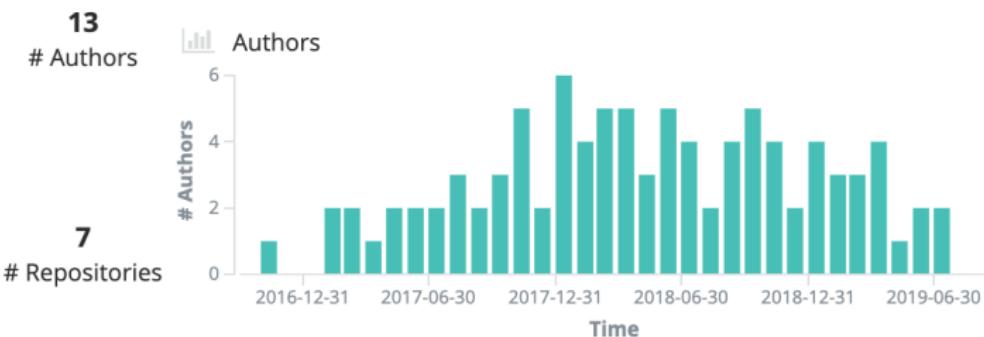
[Summary](#) [Commits](#)[Authors](#)[Repositories](#)

Figure 2: GitHub commits associated directly with this work.



Quick Statistics

Top Repositories

Repository	Commits	Authors	Organizations	Avg. Lines/Commit
				Q
https://github.com/arfc/transition-scenarios	1,560	8	1	2,172.756
https://github.com/arfc/d3ploy	703	7	1	71.853
https://github.com/arfc/ddca_numerical_exp	236	4	1	133.165
https://github.com/arfc/udb_reactor	42	1	1	321.667

Figure 3: Lines of code associated directly with this work.

Detailed Schedule



2016

- ✓ Literature review of appropriate predictive algorithms.
- ✓ Add stop and restart capabilities to Cyclus (bonus: HPC deployment addition).

2017

- ✓ Identify and rectify non-algorithmic capability gaps (e.g. specific fuel cycle process archetypes) necessary for transition simulation.
- ✓ Create d3ploy
- ✓ Add toolkit additions related for geospatial information
- ✓ Implement non-optimizing (NO) methods in d3ploy.



Detailed Schedule

2018

- ✓ Design numerical experiments (tests) for verifying Deterministic-Optimizing (DO) algorithms in the context of key transitions.
- ✓ Implement Deterministic Optimizing (DO) methods in d3ploy.
- ✓ Design numerical experiments (test) for verifying Stochastic-Optimizing (SO) algorithms in the context of key transitions.

2019

- ✓ Implement Stochastic Optimizing (SO) methods in d3ploy.
- ✓ Add additional capabilities to the predictive methods. (Buffers, reprocessing complexity handing)
- ✓ Demonstrate and compare the new capability in the context of the evaluation groups the EG 23, 24, 29, 30

Detailed Schedule



Advanced Reactors and Fuel Cycles

Repositories 92 Packages 31 Teams 8 Projects 9 Settings

Demand Driven Cycamore Archetypes Updated 6 hours ago

Filter cards

new	in progress	completed
<p>handle huff review comments 2019-chee-global#17 opened by katyhuff Comp:Core Difficulty:2-Challe... Priority:2-Normal Status:4-In Progress Type:Feature</p>	<p>Rough Draft of Key Content 2019-09-17-anl#1 opened by katyhuff Comp:Analysis Difficulty:2-Challe... Priority:1-Critical Status:4-In Progress Type:Docs</p> <p>Decommission in NO archetype. d3ploy#11 opened by FlanFlanagan Comp:Core Difficulty:2-Challe... Priority:2-Normal Status:3-Selected Type:Feature + Complete DO Implementation</p> <p>Decomm ✓ d3ploy#230 opened by FlanFlanagan Changes requested</p>	<p>updates logo to the block i, makes sure slide numbers appear 2019-chee-global#16 opened by katyhuff Comp:Core Difficulty:1-Beginner Priority:2-Normal Status:5-In Review Type:Feature</p> <p>First Draft for Global presentation 2019-chee-global#15 opened by gwenchee</p> <p>Comments on first draft of final report ddca_numerical_exp#37 opened by gwenchee Type:Docs</p> <p>Splitting up the Report ddca_numerical_exp#20 opened by gwenchee</p>

Automated as To do Manage

Automated as Done Manage

Figure 4: Project management associated with this project.

Method



Because Cyclus is Agent-Based

- Its regions and institutions have the agency to dynamically make and alter deployment decisions.
- Each agent can make their own predictions of the future based on current and past performance of the simulation.

We embedded advanced time series prediction algorithms to automatically deploy fuel cycle facilities for the user. This was implemented in `d3ploy`, an Institution agent.

Motivation



Gap in capability: User must define when support facilities are deployed

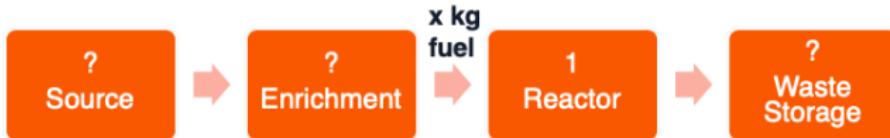


Figure 5: User defined Deployment Scheme

Bridging the gap: Developed demand-driven deployment capability in Cyclus. This capability is named d3ploy.

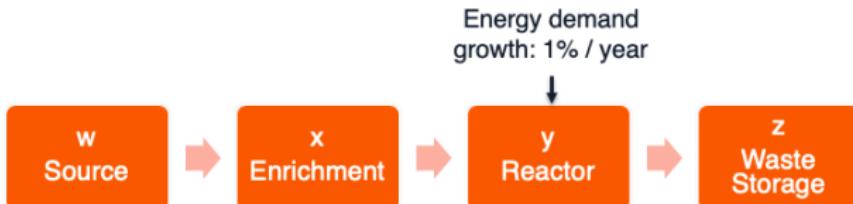


Figure 6: Demand Driven Deployment Scheme

Goals



Goals of this work

- Develop demand driven deployment capabilities in CYCLUS (d3ploy)
- Demonstrate the use of d3ploy to set up EG01-23, EG01-24, EG01-29 EG01-30 transition scenarios with constant and linearly increasing power demand curves.

Method



Because Cyclus is Agent-Based

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- Each agent can make their own predictions of the future based on current and past performance of the simulation.

We embedded advanced time series prediction algorithms to automatically deploy fuel cycle facilities for the user. This was implemented in `d3ploy`, an Institution agent.

Motivation



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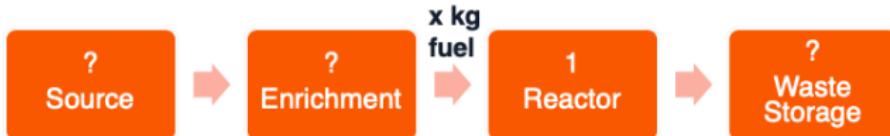


Figure 7: User defined Deployment Scheme

Bridging the gap: Developed demand-driven deployment capability in Cyclus. This capability is named d3ploy.

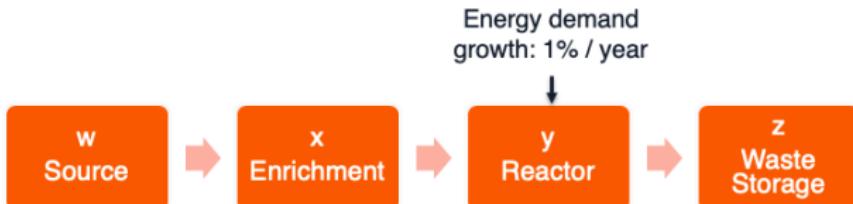


Figure 8: Demand Driven Deployment Scheme

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Cycle Simulation of historic U.S. nuclear fuel cycle

A CYCLUS simulation of the U.S. nuclear fuel cycle was created using historic United States reactor deployment data obtained from the Power Reactor Information System (PRIS) database (via IAEA).

Simulation Assumptions

Facilities present in the simulation: mine, mill, enrichment plant, fuel fabrication facility, 112 historic commercial reactors in the U.S., dry storage facility and a final waste repository.

Recipe Reactor Facility Assumptions

- *Refueling time:* 1 month
- *Cycle length:* 18 months
- *Single Spent Fuel Recipe:* 33 or 51 GWdt/MTU burnup (depletion calculations done using ORIGEN)
- *Assembly size, Core size, Batch size:* dependent on the reactor type
- *Power cap, Location:* specific to each reactor from PRIS data

CycMap: Cyclus Simulation of historic U.S. nuclear fuel cycle

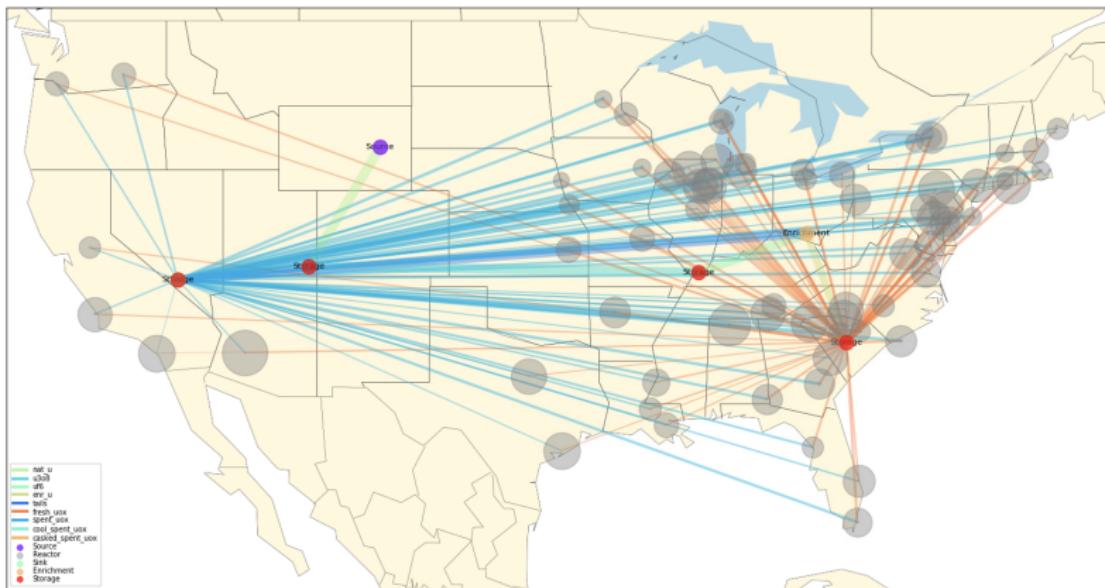


Figure 9: Cycmap of the historic Cyclus U.S nuclear fuel cycle simulation [3]

Power demand: Cyclus Simulation of historic U.S. nuclear fuel cycle

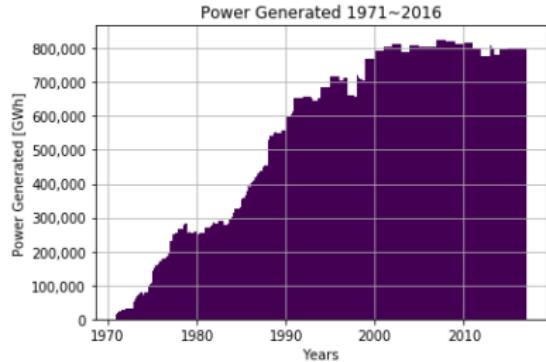


Figure 10: Power generated between 1971 and 2016 from the CYCLUS simulation

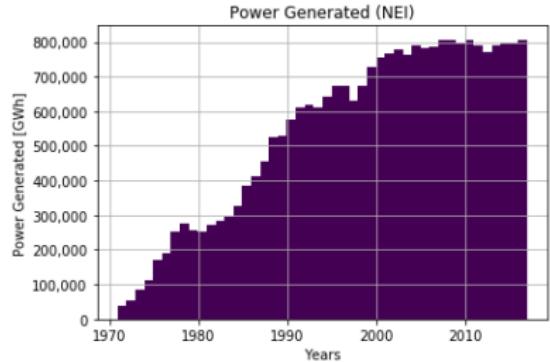


Figure 11: Power generated between 1971 and 2016 as published by the NEI [2]

Synergistic Spent Nuclear Fuel Dynamics Within the European Union

- Collaborative spent fuel management is materially feasible among nuclear nations in the European Union.
- Collaborative EU spent fuel management could expedite a fast reactor technology transition in France.
- By using spent fuel from other EU nations, France can avoid building new light water reactors to support a transition to fast reactors.



Deployment Timeline for French Transition

110 SFRs (66 GWe) are deployed by 2076.

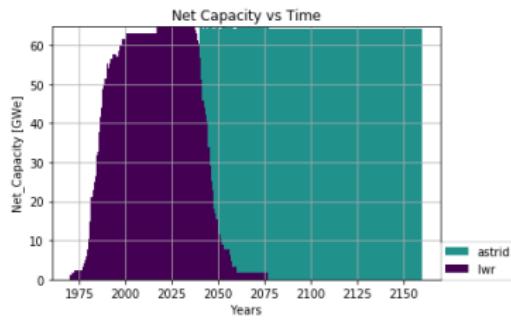


Figure 12: French Transition into an SFR Fleet

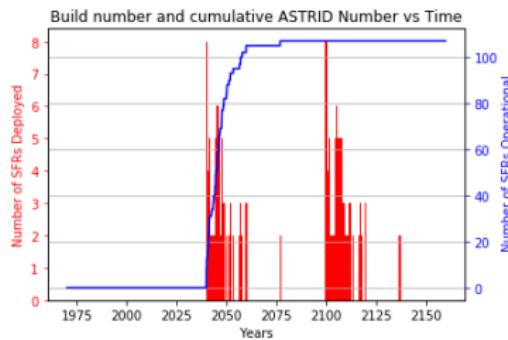


Figure 13: Deployment of French SFRs and total installed capacity

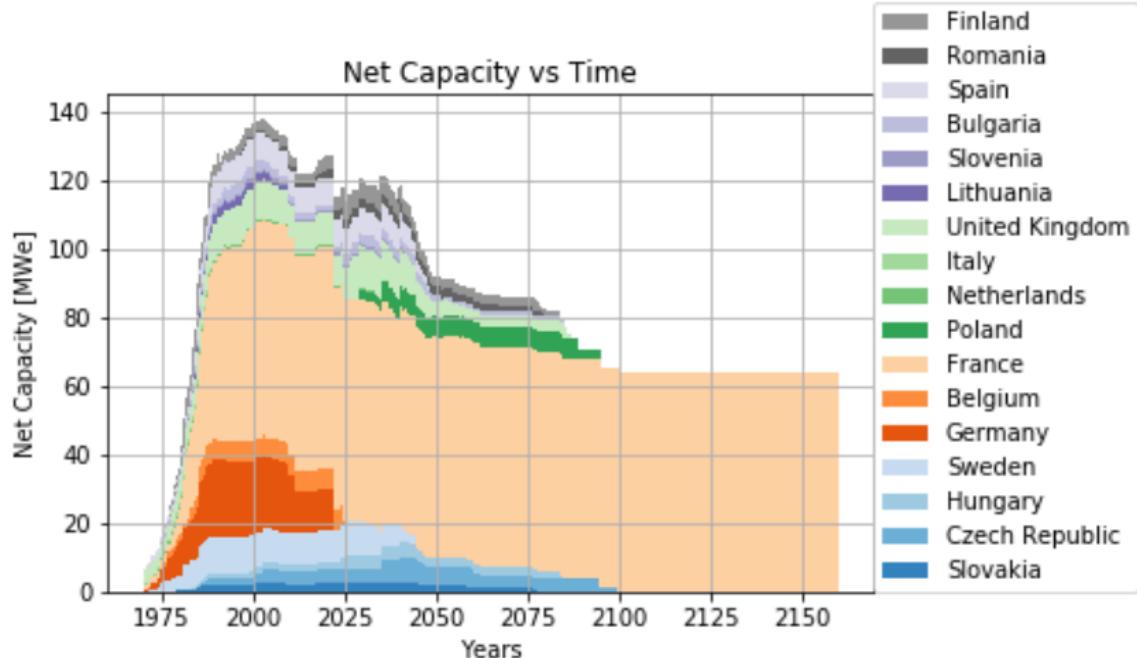


Figure 14: The simulated nuclear power deployment scheme relies on used nuclear fuel collaboration among nations. The historical operation of EU reactors is followed by the French transition to SFRs. The steep transition from 2040 to 2060 reflects the scheduled decommissioning of reactors built in the 1975-2000 era of aggressive nuclear growth in France.



d3ploy Objectives

d3ploy's Main Objective

Minimize the number of time steps of undersupply or under capacity of power.

d3ploy's Sub-Objectives

- Minimize the number of time steps of undersupply or under capacity of any commodity.
- Minimize excessive oversupply of all commodities



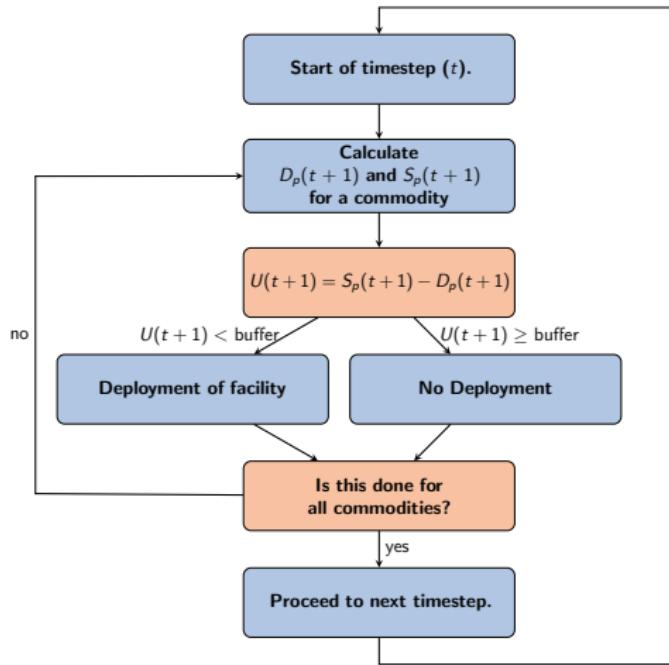
d3ploy Input Parameters

Table 1: d3ploy's required and optional input parameters with examples.

	Input Parameter	Examples
Required	Demand driving commodity	Power, Fuel, Plutonium, etc.
	Demand equation	$P(t) = 10000, \sin(t), 10000*t$
	Facilities it controls	Fuel Fab, LWR reactor, SFR reactor, Waste repository, etc.
	Capacities of the facilities	3000 kg, 1000 MW, 50000 kg
	Prediction method	Power: fast fourier transform Fuel: moving average Spent fuel: moving average
	Deployment driven by	Installed Capacity/Supply
Optional	Supply/Capacity Buffer type	Absolute
	Supply/Capacity Buffer size	Power: 3000 MW Fuel: 0 kg Spent fuel: 0 kg
	Facility preferences	LWR reactor = 100-t SFR reactor = t-100
	Facility constraint	SFR reactor constraint = 5000kg of Pu



d3ploy logic flow



D_p : PredictedDemand
 S_p : PredictedSupply
 $U = S_p - D_p$

Figure 15: d3ploy logic flow at every timestep in CYCLUS [1].



d3ploy Prediction Methods

Non-Optimizing Methods

- Moving Average (`ma`)
- Autoregressive Moving Average (`arma`)
- Autoregressive Heteroskedasticity (`arch`)

Deterministic-Optimizing Methods

- Fast Fourier Transform (`fft`)
- Polynomial Fit (`poly`)
- Exponential Smoothing
- Triple Exponential Smoothing (`holt-winters`)

Stochastic-Optimizing Methods

- Auto-Regressive Integrated Moving Averages (`ARIMA`)



Breakdown of Results

4 transition scenarios sought to minimize undersupply and under capacity of all commodities.

- ① EG01-23 ($P(t) = P_0$)
- ② EG01-24 ($P(t) = P_0 + rt$)
- ③ EG01-29 ($P(t) = P_0$)
- ④ EG01-30 ($P(t) = P_0 + rt$)

This is achieved by:

- ① Comparison of prediction methods for each of 4 scenarios is conducted to determine the best method.
- ② Sensitivity analysis of power supply buffer is conducted to determine best buffer size.
- ③ Using best prediction method, look ahead rate, buffer size, demonstrate d3ploy deploying reactor and supporting facilities to meet power demand for 4 scenarios.



Comparison of Prediction Methods

EG01-23 Constant Power Demand Transition Scenario

EG1-23: Time steps with an undersupply of each commodity for different prediction methods

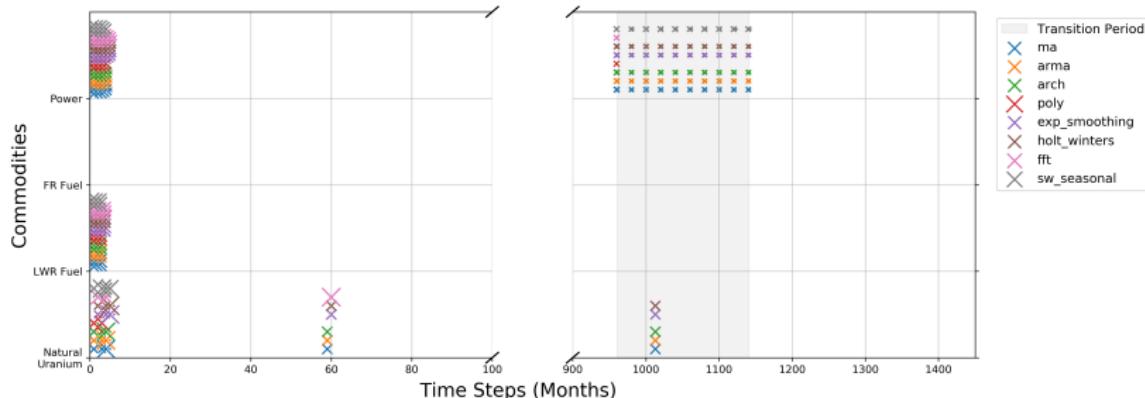


Figure 16: Time dependent undersupply of commodities for different prediction methods for the EG01-23 Transition Scenario with Constant Power Demand. The size of each cross is based on the size of the undersupply. Fewer crosses on plot indicates the method is more successful at preventing undersupply of each commodity



Comparison of Prediction Methods

EG01-23 Constant Power Demand Transition Scenario

EG1-23: Time steps with an undersupply of each commodity for different prediction methods

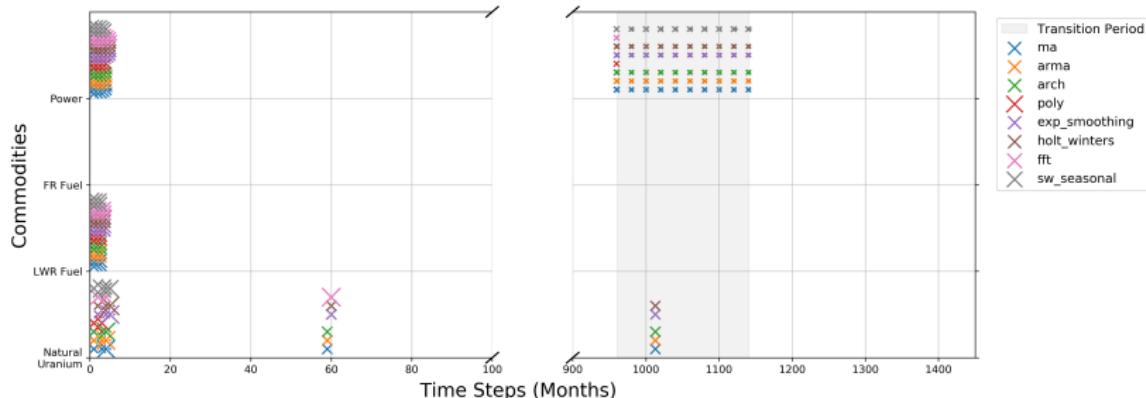


Figure 17: Time dependent undersupply of commodities for different prediction methods for the EG01-23 Transition Scenario with Constant Power Demand. The size of each cross is based on the size of the undersupply. Fewer crosses on plot indicates the method is more successful at preventing under capacity of each commodity

Comparison of Prediction Methods



EG01-24 Constant Power Demand Transition Scenario

EG1-24: Time steps with an undersupply of each commodity for different prediction methods

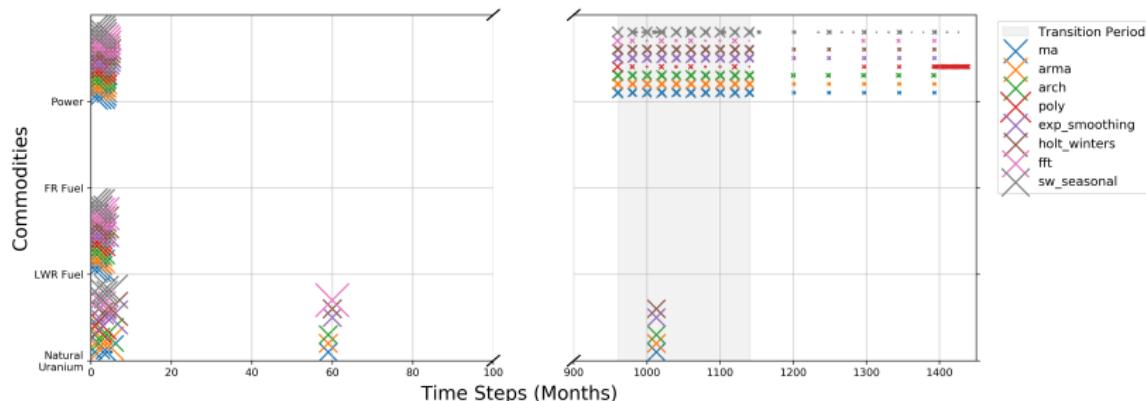


Figure 18: Time dependent undersupply of commodities for different prediction methods for the EG01-24 Transition Scenario with Linearly Increasing Power Demand. The size of each cross is based on the size of the undersupply. Fewer crosses on plot indicates the method is more successful at preventing undersupply of each commodity



Comparison of Prediction Methods

EG01-24 Constant Power Demand Transition Scenario

EG1-24: Time steps with an undersupply of each commodity for different prediction methods

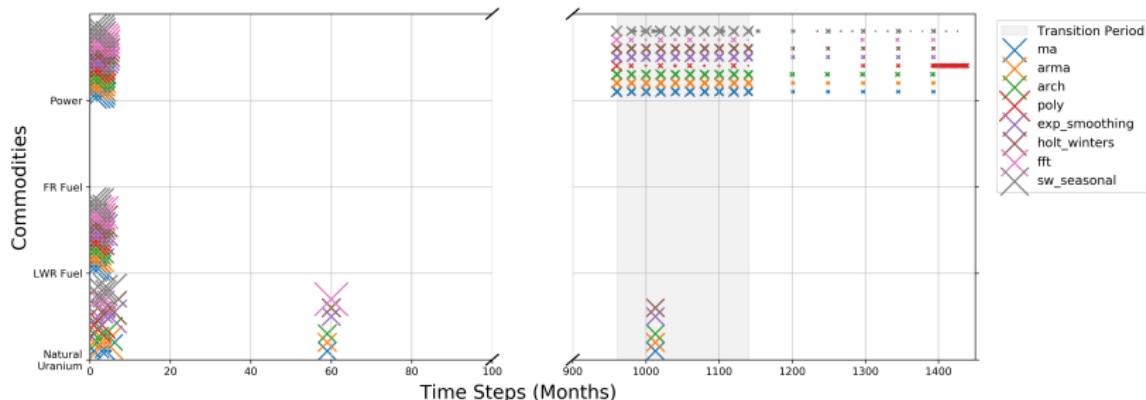


Figure 19: Time dependent undersupply of commodities for different prediction methods for the EG01-24 Transition Scenario with Linearly Increasing Power Demand. The size of each cross is based on the size of the under capacity. Fewer crosses on plot indicates the method is more successful at preventing under capacity of each commodity

Comparison of Prediction Methods



Main Takeaway

The best performing prediction method for each transition scenario is:

- ① EG01-23 Constant Power Demand: poly
- ② EG01-24 Linearly Increasing Power Demand: fft
- ③ EG01-29 Constant Power Demand: poly
- ④ EG01-30 Linearly Increasing Power Demand: fft



Sensitivity Analysis of Power Buffer

EG01-24: Linearly Increasing Power Demand

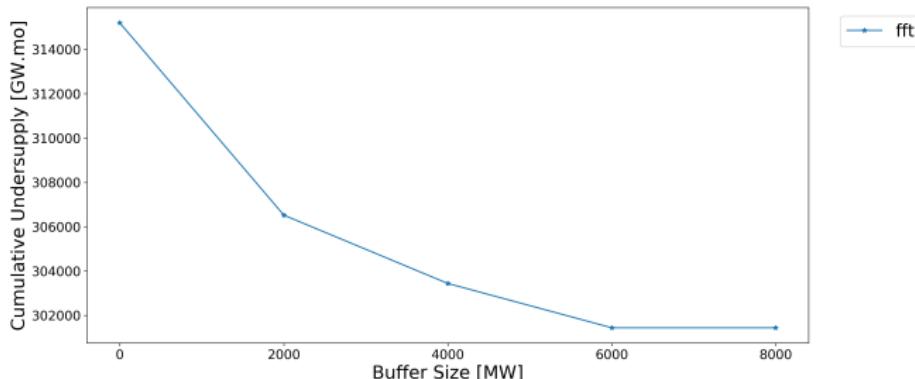


Figure 20: Sensitivity Analysis of Power buffer size on cumulative undersupply of Power for EG01-EG24 transition scenarios with linearly increasing power demand using the fft prediction method.



Sensitivity Analysis of Power Buffer

EG01-30: Linearly Increasing Power Demand

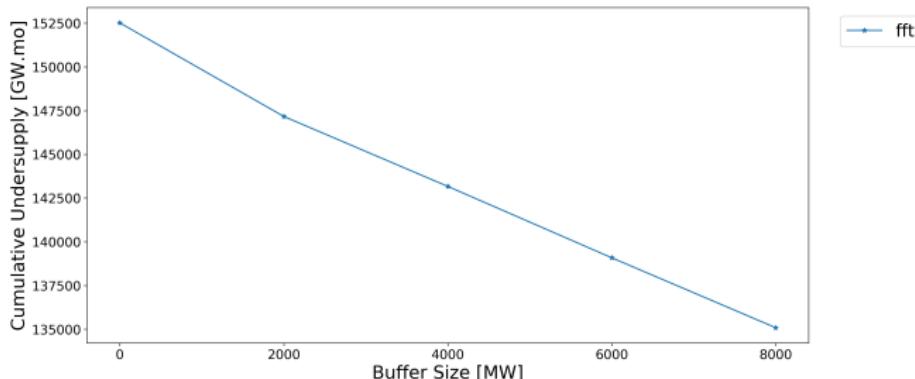


Figure 21: Sensitivity Analysis of Power buffer size on cumulative undersupply of Power for EG01-EG30 transition scenarios with linearly increasing power demand using the fft prediction method.

Sensitivity Analysis of Power Buffer



Main Takeaway

The best power supply buffer for each transition scenario is:

- ① EG01-23 Constant Power Demand: 0 MW
- ② EG01-24 Linearly Increasing Power Demand: 6000 MW
- ③ EG01-29 Constant Power Demand: 0 MW
- ④ EG01-30 Linearly Increasing Power Demand: 8000 MW



Best Performing Transition Scenarios

Input Parameters of best performing transition scenarios

	Input Parameter	Simulation Description			
		EG01-23	EG01-24	EG01-29	EG01-30
Required	Demand driving commodity	Power			
	Demand equation [MW]	60000	$60000 + 250t/12$	60000	$60000 + 250t/12$
	Prediction method	poly	fft	poly	fft
	Deployment Driving Method	Installed Capacity			
Optional	Buffer type	Absolute			
	Power Buffer size [MW]	0	6000	0	8000

Table 2: d3ploy's input parameters for EG01-EG23, EG01-EG24, EG01-EG29, and EG01-EG30 transition scenarios that minimizes undersupply of power and minimizes the undersupply and under capacity of the other facilities.



Best Performing Transition Scenarios

EG01-23: Constant Power Demand

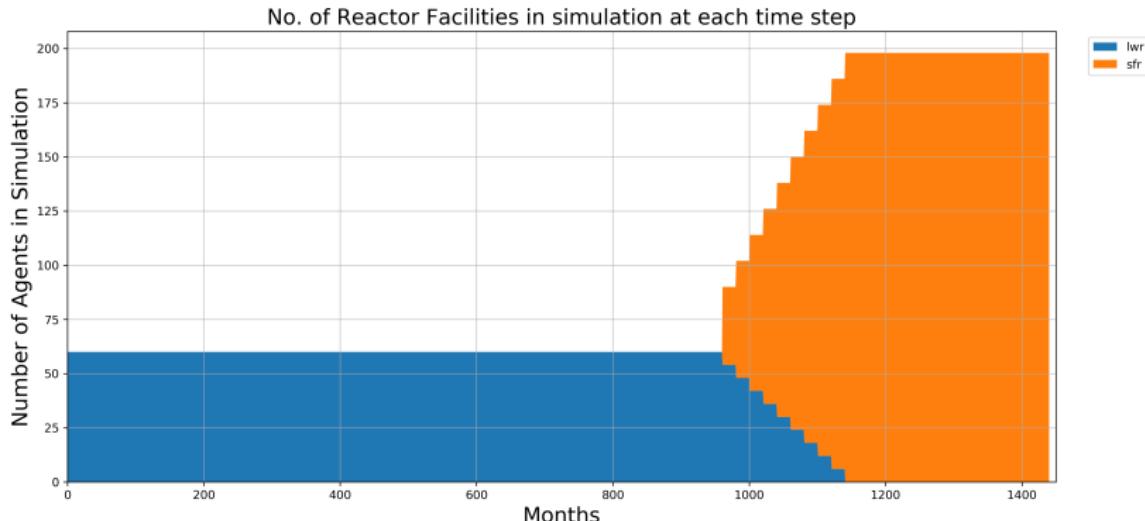


Figure 22: Time dependent deployment of reactor facilities in the EG01-23 constant power demand transition scenario. d3ploy automatically deploys reactor facilities to set up a supply chain to meet constant power demand of 60000 MW during a transition from LWRs to SFRs



Best Performing Transition Scenarios

EG01-23: Constant Power Demand

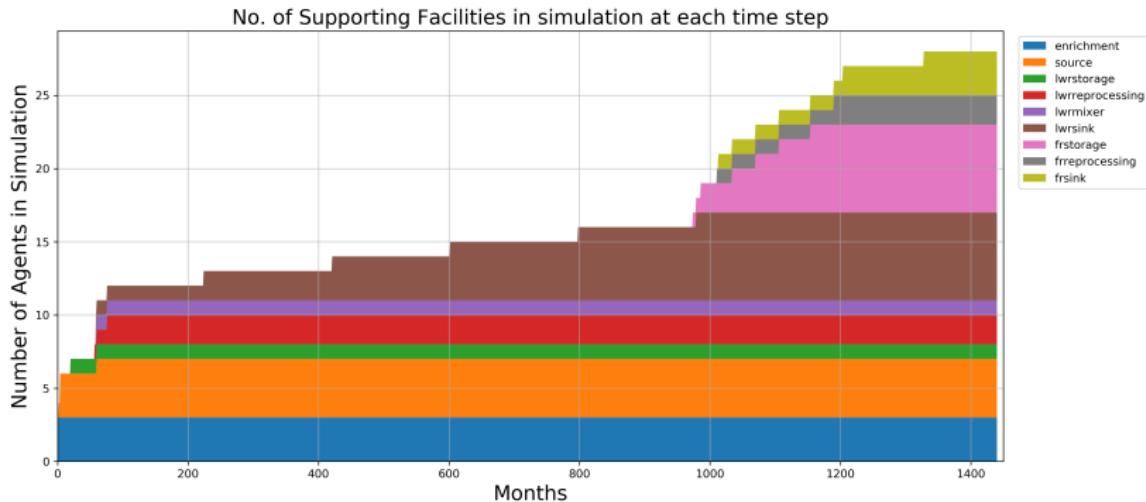


Figure 23: Time dependent deployment of supporting facilities in the EG01-23 constant power demand transition scenario. d3ploy automatically deploys reactor facilities to set up a supply chain to meet constant power demand of 60000 MW during a transition from LWRs to SFRs



Best Performing Transition Scenarios

EG01-30: Linearly Increasing Power Demand

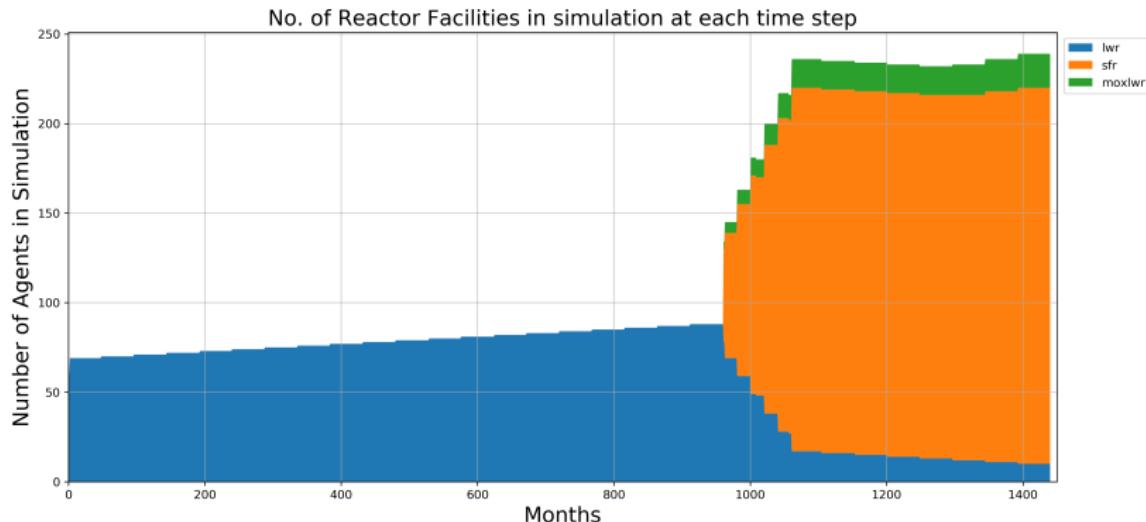


Figure 24: Time dependent deployment of reactor facilities in the EG01-30 linearly increasing power demand transition scenario. d3ploy automatically deploys reactor facilities to set up a supply chain to meet constant power demand of $60000 + 250t/12$ MW during a transition from LWRs to SFRs



Best Performing Transition Scenarios

EG01-30: Linearly Increasing Power Demand

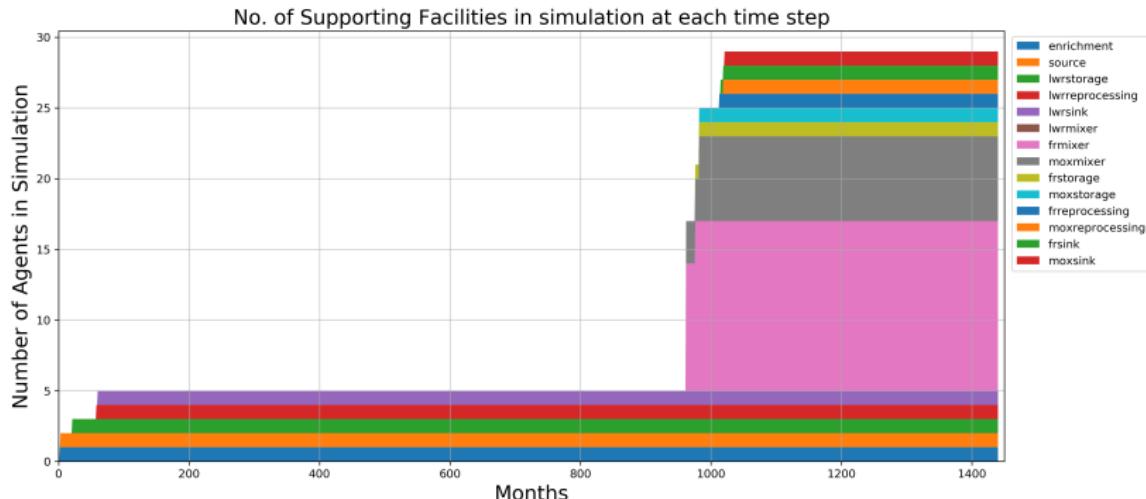


Figure 25: Time dependent deployment of supporting facilities in the EG01-30 linearly increasing power demand transition scenario. d3ploy automatically deploys reactor facilities to set up a supply chain to meet constant power demand of $60000 + 250t/12$ MW during a transition from LWRs to SFRs



Best Performing Transition Scenarios

Undersupply and under capacity of commodities for the best performing transition scenarios

Table 3: Undersupply/capacity of commodities for the best performing EG01-EG23,24,29,30 transition scenarios.

	Undersupplied Time Steps			
	EG01-EG23	EG01-EG24	EG01-EG29	EG01-EG30
Power Demand	Constant	Linearly Increasing	Constant	Linearly Increasing
Prediction Method	poly	fft	poly	fft
Power Supply Buffer [MW]	0	6000	0	8000
Commodities				
Natural Uranium	2	3	1	1
LWR Fuel	4	6	1	2
SFR Fuel	0	0	2	2
MOX LWR Fuel	-	-	2	2
Power	6	7	4	5
LWR Spent Fuel	1	1	1	1
SFR Spent Fuel	1	1	1	1
MOX LWR Spent Fuel	-	-	1	1

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Conclusion



These results demonstrate that by carefully selecting d3ploy parameters, we are able to **effectively automate deployment** of reactor and supporting facilities to set up constant and linearly increasing power demand transition scenarios for EG01-23, EG01-24, EG01-29, and EG01-30 with minimal power undersupply.

Not completely eliminating undersupply and under capacity of commodities in the simulation is expected since without time series data at the beginning of the simulation, d3ploy takes a few time steps to collect time series data about power demand to predict and start deploying reactor and supporting fuel cycle facilities.



Auxilliary Activities



2019 TECHNICAL WORKSHOP ON NUCLEAR FUEL CYCLE SIMULATION

University of Illinois at Urbana-Champaign

The 4th annual Technical Workshop on Fuel Cycle Simulation (TWOFC19) will be held June 26-28, 2019 at the *University of Illinois at Urbana-Champaign*. It is hosted by the *Advanced Reactors and Fuel Cycles group* in the Department *Nuclear, Plasma, and Radiological Engineering*.



Auxilliary Activities

Cyclus (particularly Wisconsin) is a key participant in the Functionality Isolation Test Benchmark.

- CNRS / IN2P3 (Xavier Doligez, Marc Ernoult and Nicolas Thiolière) - CLASS
- University of Wisconsin - Madison (Paul Wilson and Baptiste Mouginot) - CYCLUS
- University of South Carolina (Robert Flanagan) - CYCLUS
- University of Illinois at Urbana-Champaign (Katy Huff) - CYCLUS
- Argonne National Lab (Bo Feng) - DYMOND
- Oak Ridge National Lab (Eva E. Davidson) - ORION
- Idaho National Lab (Ross Hays) - VISION
- CIEMAT (Aris Villacorta, Francisco Alvarez) - Tr_Evol / Evol_code
- TRACTEBEL (Hubert Druenne, Bart Vermeeren) - ANICCA
- Univ. of technology and economics of Budapest (Mate Halasz, Máté Szieberth) - SITON
- Hungarian Academy of Sciences (Aron Brolly) - SITON
- Universidad Católica del Maule (Ivan Merino) - ANICCA

Acknowledgement



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References |



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Technical report, April 2018.
- [3] Gyu Tae Park, Kathryn Huff, and Kathryn Huff.
arf/cycmap : Validation of Spent Nuclear Fuel Output by Cyclus, a Fuel Cycle Simulator Code, October 2018.