DEMONSTRATION OF DEMAND DRIVEN DEPLOYMENT CAPABILITIES IN CYCLUS

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ABSTRACT

In this work, we developed demand-driven deployment capabilities in Cyclus*,* `d3ploy`*. User-controlled capabilities such as supply/capacity buffers, constraint deployment, prediction algorithms, and installed capacity deployment were introduced to give a user tools to minimize commodity undersupply in the simulation. We demonstrate* `d3ploy`*'s capability to automatically deploy fuel cycle facilities to meet various types of user-defined power demands: constant, linearly increasing, and sinusoidal.*

I INTRODUCTION

For many fuel cycle simulators, it is currently up to the user to define a deployment scheme of supporting facilities to ensure that there is no gap in the supply chain. To ease setting up nuclear fuel cycle simulations, Nuclear Fuel Cycle (NFC) simulators should bring demand responsive deployment decisions into the dynamics of the simulation logic [1]. Thus, a next generation NFC simulator should predictively and automatically deploy fuel cycle facilities to meet a user defined power demand.

Cyclus is an agent-based nuclear fuel cycle simulation framework [2]. In Cyclus, each entity (i.e. Region, Institution, or Facility) in the fuel cycle is an agent. Region agents represent geographical or political areas that institution and facility agents can be grouped into. Institution agents control the deployment and decommission of facility agents and represents legal operating organizations such as a utility, government, etc. [2]. Facility agents represent nuclear fuel cycle facilities. Cycamore [3] provides agents to represent process physics of various components in the nuclear fuel cycle (e.g. mine, fuel enrichment facility, reactor).

The Demand-Driven Cycamore Archetypes project (NEUP-FY16-10512) aims to develop Cyclus' demand-driven deployment capabilities. This capability is added as a Cyclus Institution agent that deploys facilities to meet the front-end and back-end fuel cycle demands based on a user-defined commodity demand. This demand-driven deployment capability is called `d3ploy`.

In this paper, we explain the capabilities of `d3ploy` and demonstrate how `d3ploy` minimizes undersupply of all commodities in a few simulations while meeting key simulation constraints. Constant, linearly increasing, and sinusoidal power demand transition scenarios are demonstrated. Insights are discussed to inform parameter input decisions for future work in setting up larger transition scenarios that include many facilities.

II D3PLOY CAPABILITIES

At each time step, `d3ploy` predicts demand and supply of each commodity for the next time step. Then, `d3ploy` deploys facilities to meet predicted demand. `D3ploy`'s primary objective is minimizing the number of time steps of undersupply of any commodity. Figure 1 shows the flow of `d3ploy`'s logic at every time step.

Where `d3ploy` predicts an undersupply, it responds by deploying the fewest number of available facilities to meet demand with minimal oversupply.

II.A Basic User-Defined Input Variables

The user inputs specific variables to customize their simulation. Descriptions of each input variable are found in the README of the `d3ploy` github repository [4].

Essentially, the user must define the facilities the `d3ploy` institution controls and can deploy. The user must also define the driving commodity, all facility capacities for producing that commodity, its demand equation, and which method predicts supply and demand. For example, the user can define a demand equation for power of $1000 \times timestep$ MW and `d3ploy` will deploy available reactor and supporting facilities to meet the defined power demand.

The user can also provide a time-dependent equation that governs preference for a particular facility compared to other facilities that provide the same commodity. For example, the user can define a Light Water Reactor (LWR) and a Sodium-Cooled Fast Reactor (SFR) to have preferences of $101 - timestep$ and $timestep$ respectively. The institution will prefer deployment of LWR facilities over SFR before time step 51.

The user can constrain facility deployment until a sizable inventory of a specific commodity is accumulated. The user can also define an initial facility list of facilities that are present in the institution at the beginning of the simulation.

II.B Prediction Algorithms

Three interchangeable algorithm classes govern demand and supply predictions: non-optimizing, deterministic optimizing, and stochastic optimizing.

Three methods were implemented in the non-optimizing

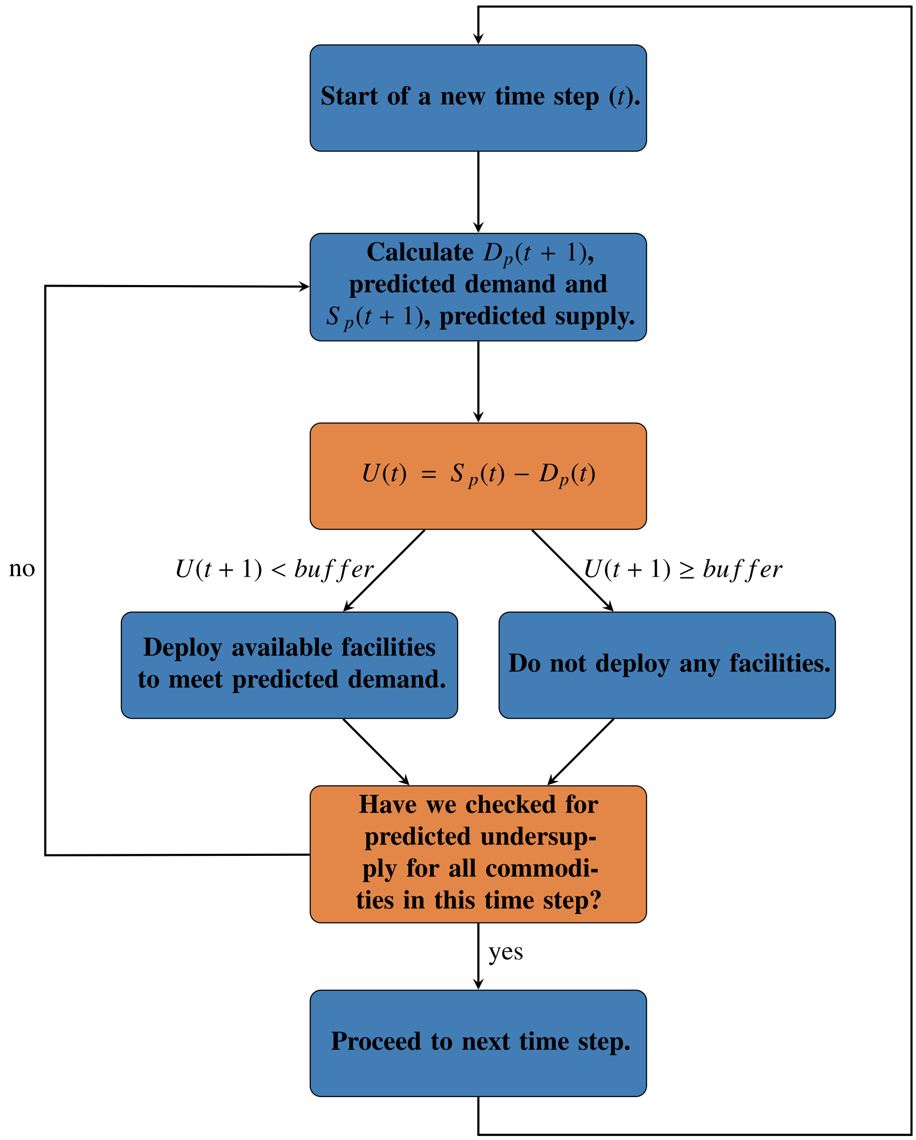

Fig. 1: `D3ploy` logic flow at each time step in Cyclus.

class: moving average (MA), autoregressive moving average (ARMA), and autoregressive conditional heteroskedasticity (ARCH). Four methods were implemented in the deterministic optimizing class: Polynomial fit regression, simple exponential smoothing, triple exponential smoothing (holt-winters), and fast fourier transform (fft). One method was implemented for stochastic optimizing model: stepwise seasonal.

The user can choose which prediction algorithm governs each `d3ploy` facility. The effectiveness of a prediction algorithm depends on the type of power demand in a scenario and the type of commodity (demand driving commodity vs non-driving commodity, demand driven deployment vs supply driven deployment etc.). For example, the most effective method for predicting demand and supply for the power commodity in a scenario with a sinusoidal power demand is the triple exponential smoothing method. However, for the non-driving commodities in the same scenario, the fast fourier transform method is more effective than triple exponential smoothing. This paper will comment on these categories of problems and their suitable algorithms.

II.C Demand-driven vs. Supply-driven Institutions

Within `d3ploy`, there are two institutions: `DemandDrivenDeploymentInst` and `SupplyDrivenDeployment.Inst`. The prior is used for the front-end of the fuel cycle and the latter is used for the back-end. For example, for front end facilities, the reactor demands fuel and `DemandDrivenDeploymentInst` triggers the deployment of fuel fabrication facilities to create supply meeting the demand for fuel. For back end facilities, the reactor generates spent fuel and `SupplyDrivenDeploymentInst` triggers the deployment of waste repository facilities to create capacity for storage of the supply of spent fuel.

TABLE I: Transition scenario parameters that are consisted for constant, linear increasing and sinusoidal power demand simulations

Parameters	**Description**
Facilities Present	`Source` (Capacity: 3000kg), `Reactor` (Capacity: 1000MW), `Sink` (Capacity: 50000kg)
New Reactor Parameters	Cycle time: 18 months, Refuel time: 1 month
Driving Commodity	Power

TABLE II: Constant Power Demand Transition Scenario's Parameters

	Parameters	**Description**
Overall	Demand Equation	10000 MW
Power Commodity	Prediction Method	Fast Fourier Transform
	Supply Buffer	3000 MW (3 reactor capacities)
Fuel Commodity	Prediction Method	Moving Average
	Supply Buffer	0 kg
Spent Fuel Commodity	Prediction Method	Moving Average
	Capacity Buffer	0 kg

II.D Installed Capacity

The user can choose between deploying facilities based on the difference between predicted demand and predicted supply or predicted demand and installed capacity. There are two advantages to use installed capacity over predicted supply. The first is for facilities that provide intermittent supply, such as a reactor facility that has a designated refueling time. During time steps in which a reactor is refueling, the user might not want `d3ploy` to deploy more facilities to make up for the lack of supply caused by this one time step gap in supply. The second is for situations where the input commodity for a facility has run out and the facility that produces the input commodity is no longer commissionable. Therefore, with the demand for the output commodity of that facility, `d3ploy` would deploy that facility to meet the demand, however due to the lack of the input commodity, even if there are infinite numbers of that facility, it will not produce the output commodity. For example, in a transition scenario from LWRs to fast reactors, the fast reactor demand for Pu may exceed the inventory provided by LWRs before they were decommissioned. This will result in the deployment of mixer facilities that generate the fast reactor fuel despite the lack of plutonium to generate the fuel. This can be avoided by constraining fast reactor facility deployment until a sizable inventory of Pu is accumulated.

II.E Supply/Capacity Buffer

In `DemandDrivenDeploymentInst`, the user can choose to provide a buffer for predicted supply. `D3ploy` will deploy facilities to meet the predicted demand with the additional buffer. In `SupplyDrivenDeploymentInst`, the user can choose to provide a buffer for predicted capacity. `D3ploy` will deploy facilities to meet the predicted supply with the additional buffer. For example, the user could set the power commodity's supply buffer to be 2000 MW. If predicted demand is 10000 MW, `d3ploy` will deploy reactor facilities to meet the predicted demand and supply buffer, resulting in a power supply of 12000 MW. The buffer can be defined as a percentage value (equation 1) or an absolute value (equation 2).

$$S_{pwb} = S_p * (1 + d) \qquad (1)$$

$$S_{pwb} = S_p + a \qquad (2)$$

where S_{pwb} is predicted supply/capacity with buffer, S_p is the predicted supply/capacity without buffer, d is the percentage value in decimal form, and a is the absolute value of the buffer.

Using a combination of this buffer capability with the installed capacity deployment driving method in a transition scenario simulation is effective in minimizing undersupply of a commodity without having excessive over supply.

III DEMONSTRATION OF D3PLOY CAPABILITIES

Constant, linearly increasing, and sinusoidal power demand simulations are shown to demonstrate `d3ploy`'s capabilities. A balance between the various system parameters must be met for each type of simulation to meet the goal of minimizing undersupply and under capacity for the various commodities. The input files and scripts to produce the plots in this paper can be reproduced using [4].

These simulations are basic transition scenarios that only include three types of facilities: `source`, `reactor` and `sink`. All of the simulations begin with ten reactor facilities, `reactor1` to `reactor10`. These reactors have staggered cycle lengths and lifetimes so that they do not all refuel and decommission at the same time steps. When the ten initial reactor facilities begin to decommission, `d3ploy` deploys reactor facilities of `newreactor` type to meet unmet demand for power. All the simulations deploy facilities based on the relationship between predicted demand and installed capacity. This capability was discussed in the previous section. Table I shows the simulation parameters that are consistent across all the discussed scenarios.

These basic transition scenarios were set up to demonstrate `d3ploy`'s capabilities for simulating transition scenarios and to inform decisions about input parameters when setting up larger demand transition scenarios with many facilities.

III.A Transition Scenario: Constant Demand

In this section, a constant power transition scenario is shown. Table II shows the simulation parameters used in this transition scenario.

Figures 2a, 2b and 2c demonstrate `d3ploy`'s capability to deploy reactor and supporting facilities to meet the user determined power demand and subsequently demanded secondary commodities with minimal undersupply. Table III shows the number of undersupplied timesteps. In figure 2a, there are no time steps in which the supply of power falls under demand. By using a combination of the fast fourier transform method for predicting demand and setting the supply buffer to 3000MW (the capacity of 3 reactors), the user minimizes the number of undersupplied time steps of every commodity. To ensure there is no undersupply, it is important to perform a sensitivity analysis of the size of buffer to use for each commodity.

In figure 2b, a facility with a large fuel throughput is initially deployed to meet the large initial fuel demand for the starting up of ten reactors. `D3ploy` is prevented from deploying many supporting facilities that end up being redundant at the later parts of the simulation, by having an initial facility with a large throughput exist for the first few time steps in the simulation. This is a reflection of reality in which reactor manufacturers will accumulate an appropriate amount of fuel inventory before starting up reactors. There is one time step where there is an undersupply after the decommissioning of the large initial facility. This is unavoidable since the prediction methods in `d3ploy` are unable to predict this sudden drop in demand.

III.B Transition Scenario: Linearly Increasing Demand

In this section, a transition scenario with a linearly increasing power demand is shown. Table IV shows the simulation parameters used in this transition scenario.

Figures 3a, 3b and 3c demonstrate the capability of `d3ploy` to deploy reactor and supporting facilities to meet the power demand and subsequently demanded secondary commodities for a linearly increasing power demand. The fast fourier transform method for predicting power demand is used for this scenario which is identical to what was used for the constant power demand transition scenario. A smaller supply buffer could be used while still minimizing under supply.

III.C Transition Scenario: Sinusoidal Demand

In this section, a transition scenario with sinusoidal power demand is shown. A sinusoidal power demand is the reflection of power demand in the real world where power usage is higher in the winter and summer and lower in the spring and fall. Table V shows the simulation parameters used in this transition scenario.

Figures 4a, 4b and 4c demonstrate the capability of `d3ploy` to deploy reactor and supporting facilities to meet the power demand and subsequently demanded secondary commodities for a sinusoidal power demand.

For a sinusoidal power demand, the use of the triple exponential method for predicting demand is more effective than the fast fourier transform method which was used for the constant and linearly increasing power demand transition scenarios. This is because the triple exponential smoothing method excels in forecasting data points for repetitive seasonal series of data.

IV CONCLUSION

This paper describes the capabilities of `d3ploy`, demonstrates the use of `d3ploy` for an assortment of transition scenarios: constant power demand, linearly increasing power demand and sinusoidal power demand. It also provides insights on input parameter to ease the setting up of larger transition scenarios that include many facilities. Future work includes setting up similar power demand transition scenarios for extended nuclear fuel cycles that incorporate reprocessing facilities etc. A more realistic transition scenario could be explored such as an increasing power demand that has a sinusoidal pattern to represent seasons in a year for a growing power demand trend.

V ACKNOWLEDGEMENTS

This research is funded by the Department of Energy (DOE) Office of Nuclear Energy's Nuclear Energy University Program (Project 16-10512, DE-NE0008567) "Demand-Driven Cycamore Archetypes". The authors want to thank members of the Advanced Reactors and Fuel Cycles (ARFC) group at the University of Illinois at Urbana-Champaign. We also thank our colleagues from the CYCLUS community, particularly those in the University of Wisconsin Computational Nuclear Engineering Research Group (CNERG) and the University of South Carolina Energy Research Group (ERGS) for collaborative CYCLUS development.

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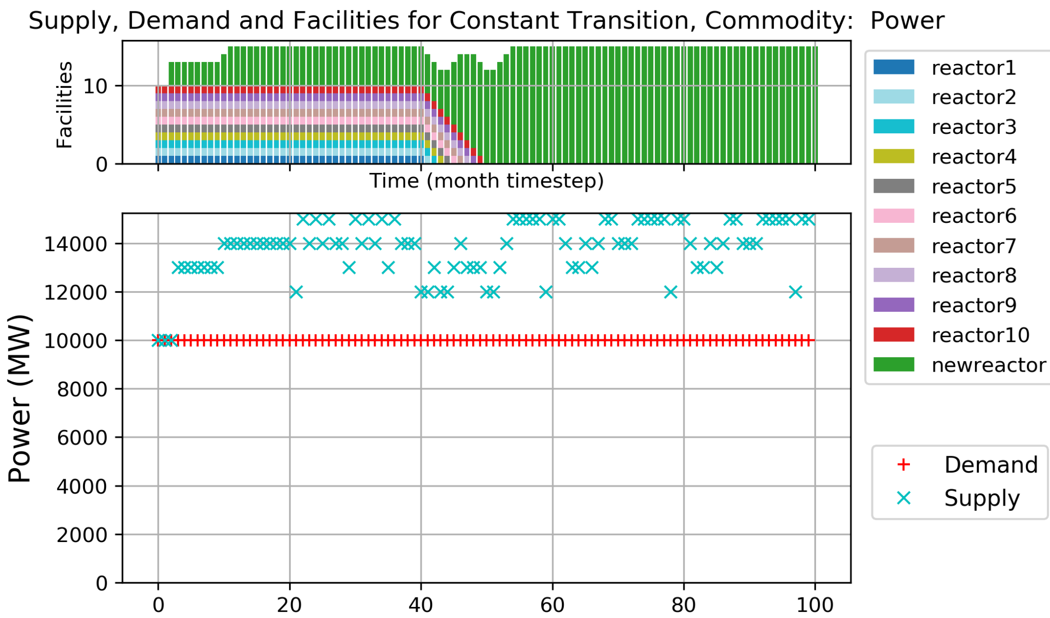
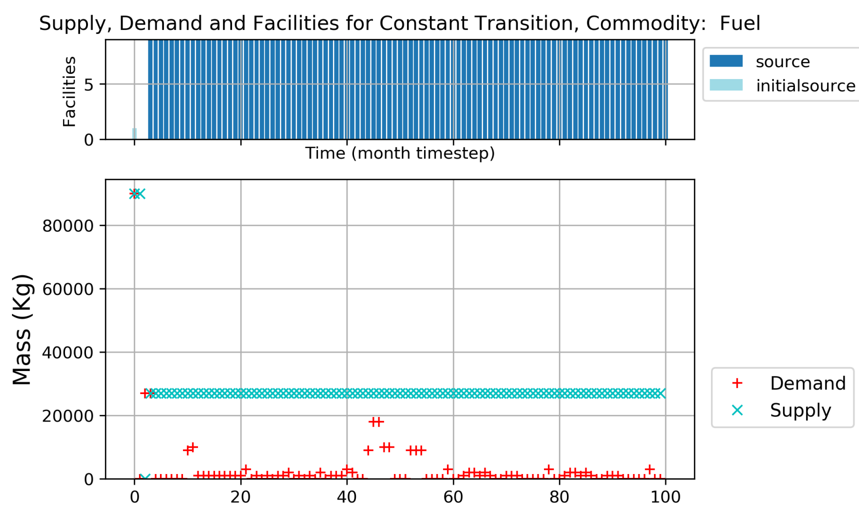
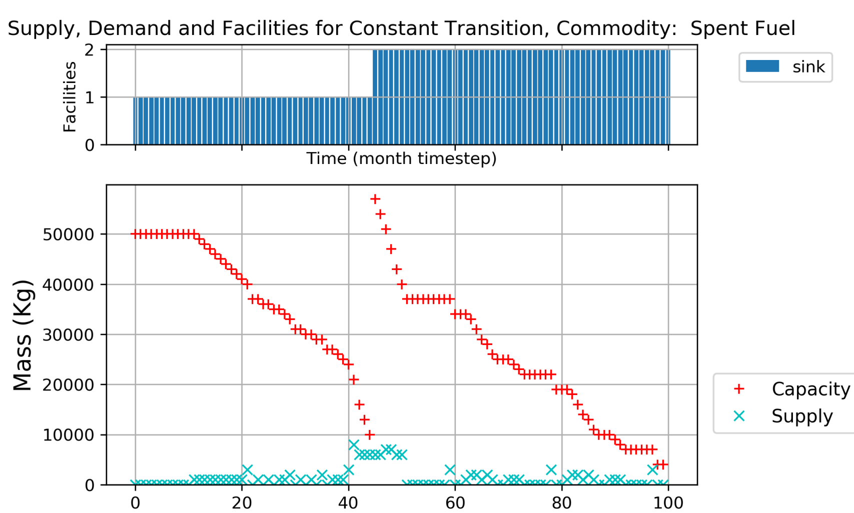


(a) The power demand is a user-defined equation and power is supplied by the reactors.

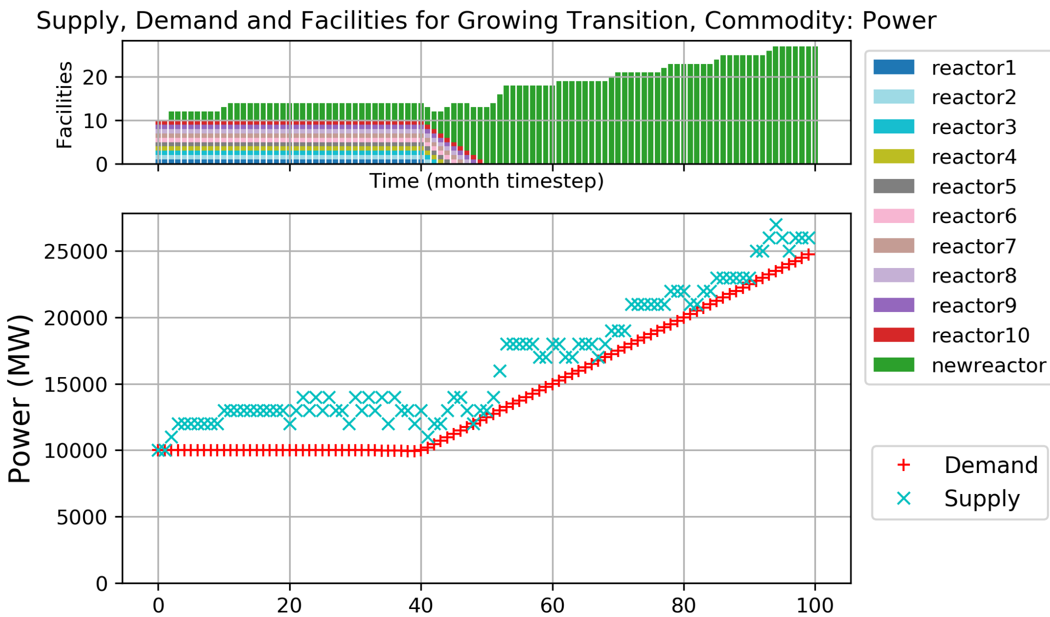


(b) Fuel is demanded by reactors and supplied by source facilities.

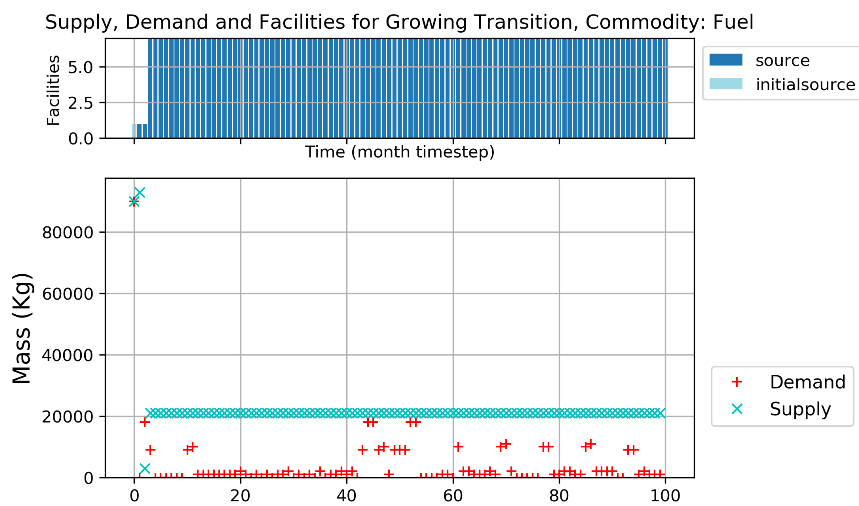


(c) Spent Fuel is supplied by reactors and the capacity is provided by sink facilities.

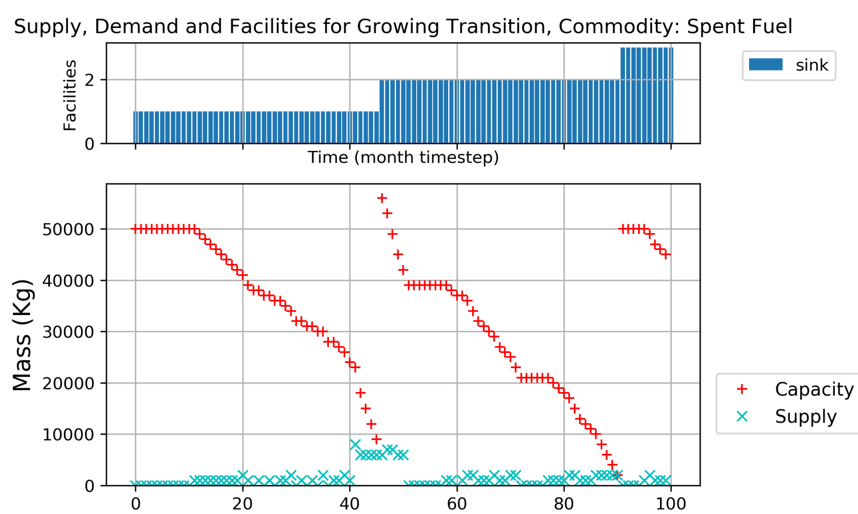
Fig. 2: Transition Scenario: Constant Power Demand of 10000MW



(a) The power demand is a user-defined equation and power is supplied by the reactors.

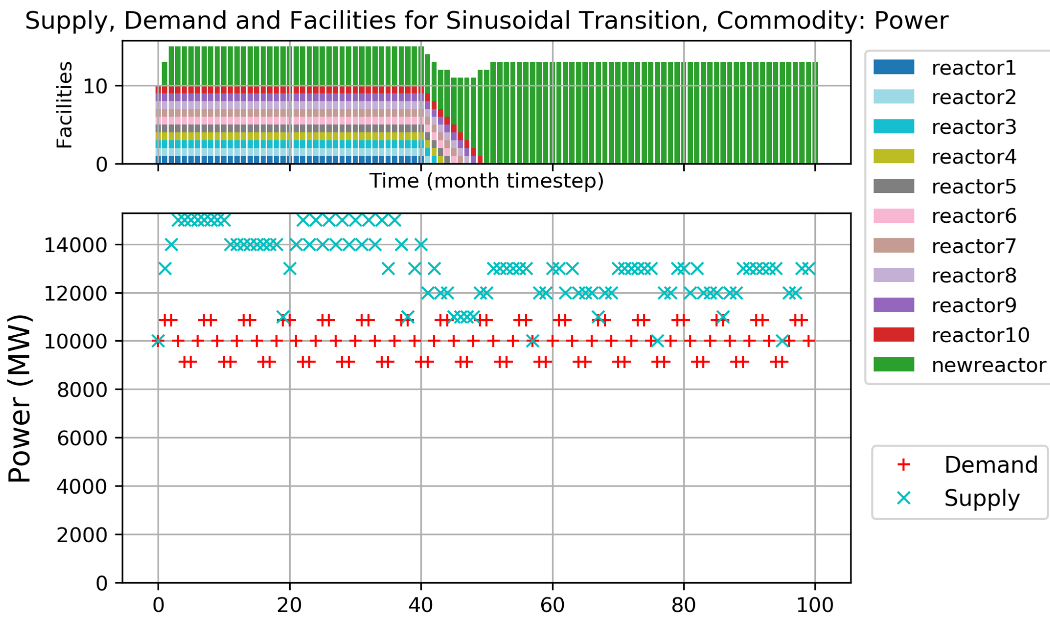


(b) Fuel is demanded by reactors and supplied by source facilities.

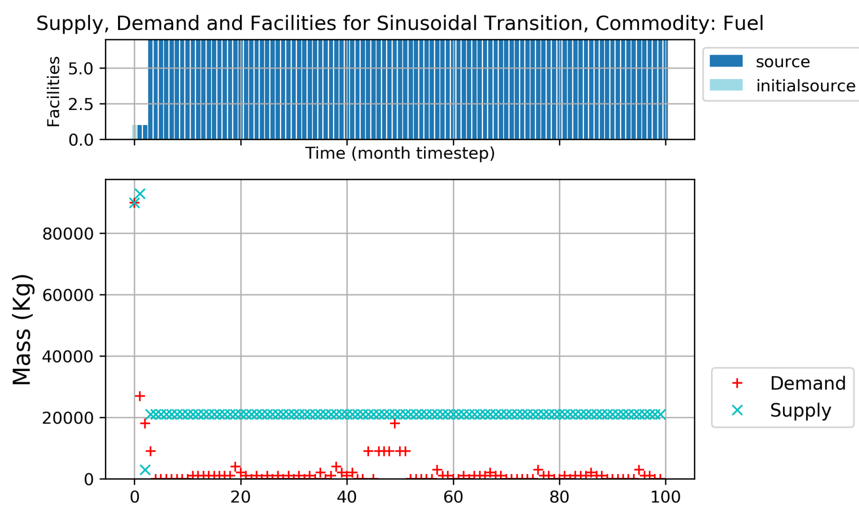


(c) Spent Fuel is supplied by reactors and the capacity is provided by sink facilities.

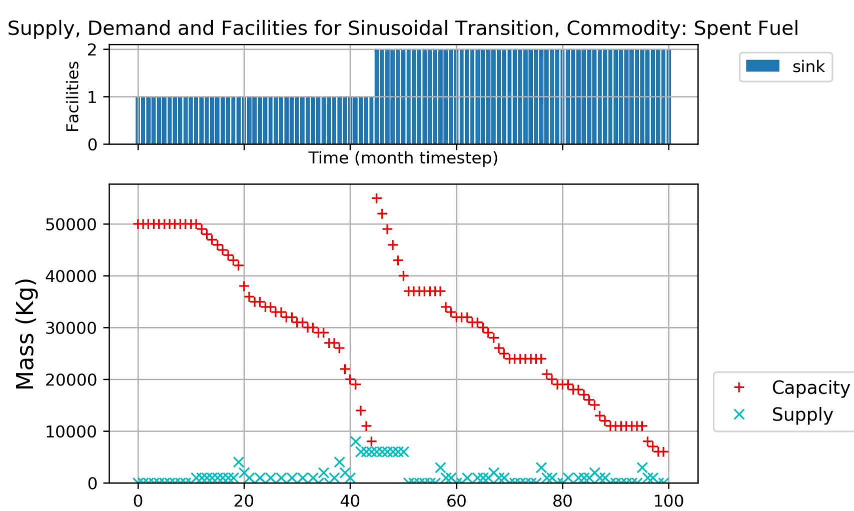
Fig. 3: Transition Scenario: Linearly increasing power demand.



(a) The power demand is a user-defined equation and power is supplied by the reactors.



(b) Fuel is demanded by reactors and supplied by source facilities.



(c) Spent Fuel is supplied by reactors and the capacity is provided by sink facilities.

Fig. 4: Transition Scenario: Sinusoidal Power Demand

TABLE III: Undersupply results for each commodity in each scenario

Transition Scenario	**Commodity**	**No. of time steps with under-supply**
Constant Power	Fuel	1
	Power	0
	Spent Fuel	0
Linearly Increasing Power	Fuel	1
	Power	0
	Spent Fuel	0
Sinusoidal Power	Fuel	1
	Power	1
	Spent Fuel	0

TABLE IV: Linearly Increasing Power Demand Transition Scenario's Parameters

	Parameters	**Description**
Overall	Demand Equation	Time<40: 10000 MW, Time>40: 250*t MW
Power Commodity	Prediction Method	Fast Fourier Transform
	Supply Buffer	2000 MW (2 reactor capacities)
Fuel Commodity	Prediction Method	Moving Average
	Supply Buffer	1000 kg
Spent Fuel Commodity	Prediction Method	Fast Fourier Transform
	Capacity Buffer	0 kg

TABLE V: Sinusoidal Power Demand Transition Scenario's Parameters

	Parameters	**Description**
Overall	Demand Equation	$1000sin(\frac{\pi*t}{3}) + 10000$
Power Commodity	Prediction Method	Triple Exponential Smoothing
	Supply Buffer	2000 MW (2 reactor capacities)
Fuel Commodity	Prediction Method	Moving Average
	Supply Buffer	1000 kg
Spent Fuel Commodity	Prediction Method	Fast Fourier Transform
	Capacity Buffer	0 kg

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