Signatures and Observables of Nuclear Fuel Cycle

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Objectives

- Create high-fidelity reprocessing facility agent models (both aqueous and electrochemical/pyroprocessing).
- Apply these models in Cyclus to simulate material diversion in closed fuel cycles.
- Identify and characterize non-traditional signatures and observables in these facilities.
- Extend successful algorithms for modeling diversion and diversion detection.
- Characterize required detection sensitivities and corresponding false positive rates.

Background

Figure 1 shows a closed nuclear fuel cycle in which each process facility presents an opportunity for diversion and proliferation.

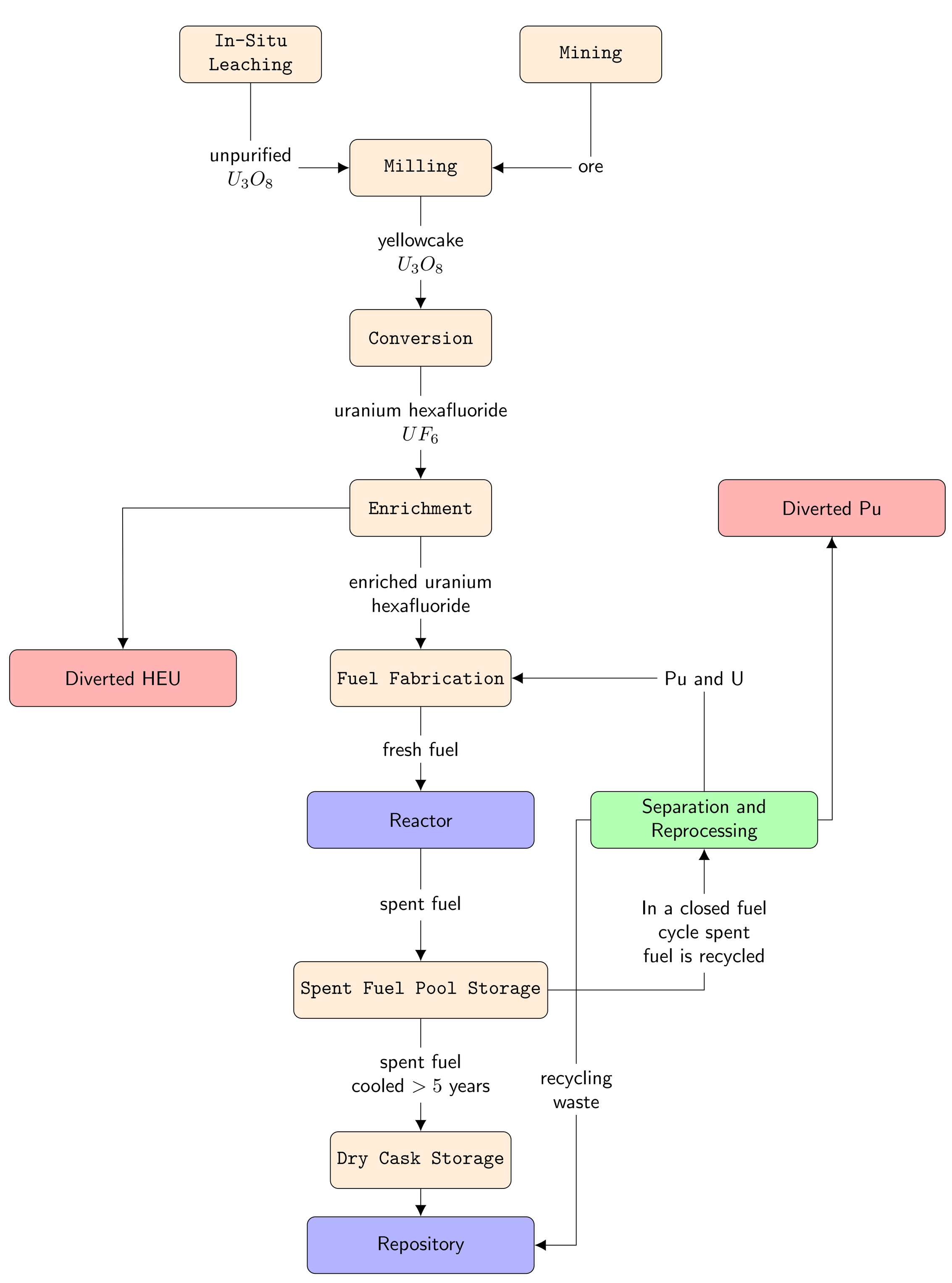

Figure: Typical Nuclear fuel cycle without diversion [3].

Cyclus

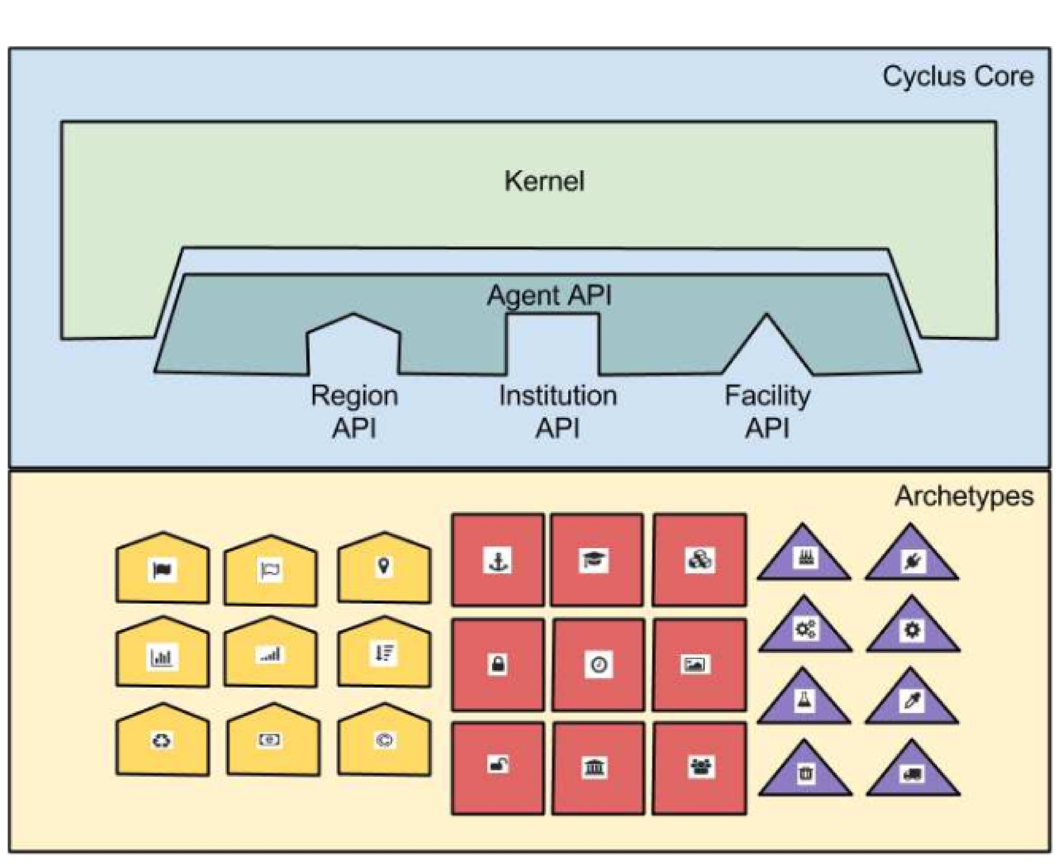

Figure: Cyclus API allows for modular build of simulations [3]

Signatures and Observables

Detection modes vary between each facility type, requiring a specific analysis of each processing plant to determine effective signatures and observables. For example, **pyroprocessing** has four major systems with observable waste: electroreduction, electrorefining, electrowinning, and metal fuel fabrication[1]. These systems have the corresponding signatures:

Direct

- **Metal Waste:** Solid, insoluble metal fission products.
- **Ceramic Waste Electrowinning:** Waste salt LiCl-KCl contains trace amounts of ^{135}Cs and ^{137}Cs from electrowinning the fuel.
- **Vitrified Waste:** LiCl-KCl salt that contains TRU and Sr alongside rare-earth elements precipitated into gases and vitrified with borosilicate glass.
- **Ceramic Waste Electroreduction:** Through electroreduction, Li_2CO_3 is used to separate ^{135}Cs, ^{137}Cs, ^{129}I and ^{14}C which are solidified into ceramic waste.

Indirect

- **Power Draw:** Sign of overusing centrifuges [7, 2].
- **Smoke Production:** Reactor producing high power than rated or reported for possible nefarious reasons [7].
- **Decay Heat:** Lower decay heat in casks signifies over-reporting of waste [5].
- **Trace Quantities:** ^{135}Xe and ^{85}Kr are commonly emitted through processing along with tritium from reactors. Need sensitive equipment but difficult to hide [1, 5].

Previous Work

Two new approaches to online diversion detection have recently been proposed [2, 7]. Which rely on power demand signatures. To facilitate online detection properties are as follows [7]:

- Product enrichment
- Frequency of shipments
- Time to production

The first proposed method uses maximum likelihood estimation to determine unreported routes of transport [2].

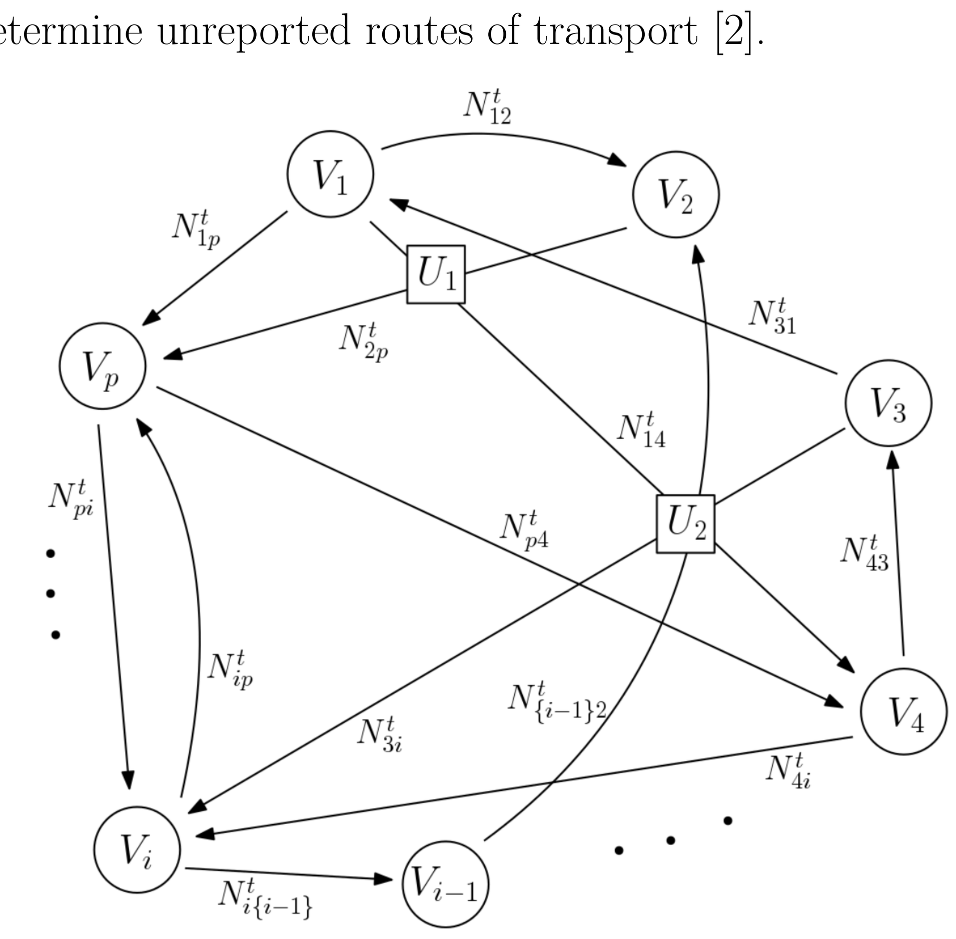

Figure: Maximum Likelihood Estimation nodal representation proposed by Hou et al[2].

Figure 4 is a visual representation of a maximum likelihood network. The second approach instead assumes a Poisson distribution [7]. Combining these properties, expected values are derived using distributions for enrichments and shipment speeds.

Prior work also exists in prevention of shadow fuel cycles through analysis of varying plant archetypes [6]. Rossi concludes that changing the material type such that technical difficulty is increased decrease in risk.

Future Work

The goal of this poster is to outline the ground work done and review previous material on diversion, particularly related to pyroprocessing. What needs to be accomplished proceeding this work is as follows:

- Simulate pyroprocessing plant and network.
- Create Cyclus output and compare to prior algorithms.
- Assess capability of using Cyclus as online detection.

Timeline

Jan. 2018	Project start:	Literature Review.
Feb. 2018	Model development:	Pyro Separations
Mar. 2018	Data collection:	Pyro Separations
May. 2018	Model development:	Cyclus Pyroprocess
Jun. 2018	Model development:	Build Archetype
Jul. 2018	Model development:	Signatures Class
Aug. 2018	Data collection:	Cyclus Simulation
Sep. 2018	Scenario simulation:	Prior Observables
Oct. 2018	Scenario simulation:	Proposed Observables
Dec. 2018	Scenario simulation:	Vary algorithm
2019	Sensitivity analysis:	Vary key parameters.

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