A Customizable Reinforcement Learning Environment for Semiconductor Fab Simulation

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This work if a result of a collaborative project between the **University of Klagenfurt** and **Infineon Technologies Austria**.

Introduction

- Goal: optimise operations of semiconductor fabs

Dispatching

- Rules created by field experts
- Optimal scaling properties
- No information about solution quality

Simulation

- Fast, cost effective
- Helps to
  - analyse effects of
    - factory upgrades
    - policy changes
    - breakdowns
    - critical decisions
  - compare methods

Planning

- Modelling effort by field experts
- Optimal solution
- Scaling issues for large-scale instances

Background

- Open datasets available (e.g. SMT2020[1])
- Simulations in industry: commercial software
- Research: small-scale (*toy*) problem with custom simulators *or* commercial software

reproducibility not possible with closed-source software licenses, versions

no customisation opportunities for commercial tools — involvement of developers required

difficulties in comparing novel methods, measuring scientific progress

arbitrary reference implementations

Goal of our research project

Develop a universal simulator for fab scheduling research from prototyping to large-scale simulations for various dispatching and scheduling strategies.

Current paper

Introduction of our Reinforcement Learning Framework.

The SMT2020 Dataset

- 4 instances
  - high volume — low mix
  - low volume — high mix
  - + extensions with development lots

- Scale of datasets
  - 107 machine families
  - 1 300 + machines
  - 40 000 lots (for 2-year period)
  - 4 to 10 products
  - 300 to 600 steps / product

The Simulator

PySCFabSim[2]: open-source, scalable, customisable simulator in Python
https://github.com/prosysscience/PySCFabSim-release

open-source	custom integrations	reproducible
pre-defined interfaces	full data access	verified
scalable	super fast	multiple datasets
reentrant flow	batch machines	cascade machines
breakdowns	dedications	sequence-dependent setups

Validation & Performance

- Validation
  - Comparison to SMT2020 dataset reference results ✅
- Performance
  - example: 2 years of operation
    - 40 000 lots, average 500 steps / lot => 10 000 000 operations
    - simulated in 20 minutes
  - usable for machine learning methods with high sample complexity, parallelisation requirements
  - 4 seconds of startup time, 100-200 MB of memory usage / thread

Machine Learning for Dispatching

- Dispatching strategies
  - involves human expertise (engineering, experience)
  - optimality unknown
  - no automatic adaption to changing circumstances
- Dispatching with ML
  - higher upfront cross (engineering, training)
  - larger policy space
  - automatic adaption of policy to process changes

The RL Framework

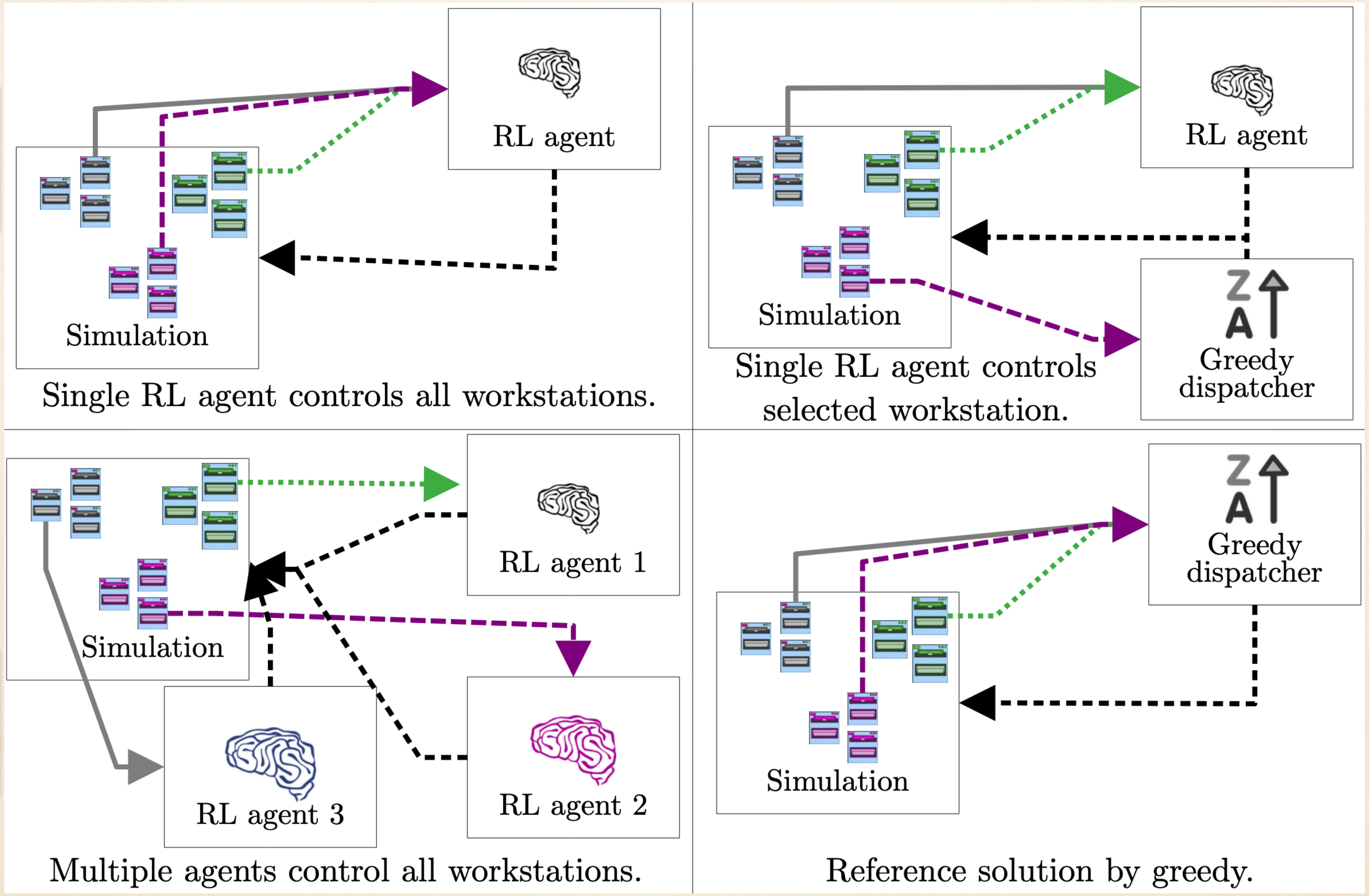
- (Why) Reinforcement Learning
  - learn from problem structure, instance characteristics
    - offline: pre-collected samples
    - online: live system
    - transfer: simulations
  - real-time dispatching

- Our RL toolbox
  - Customisable *gym* interface for the introduced simulator
    - Action
    - Observation space
    - Reward
  - „Plug-and-play“ environment
  - Single- and multi-agent configuration options
  - Partially observable

Operation Modes: Single- or Multi-Agent

Full RL control

Partial RL control



Full RL control

Heuristic control

Architecture of the RL-Framework

Main program

1. Create RL environment
2. Instantiate simulation
3. Start simulation

Simulator

4. Simulate events
5. Stop at decision point

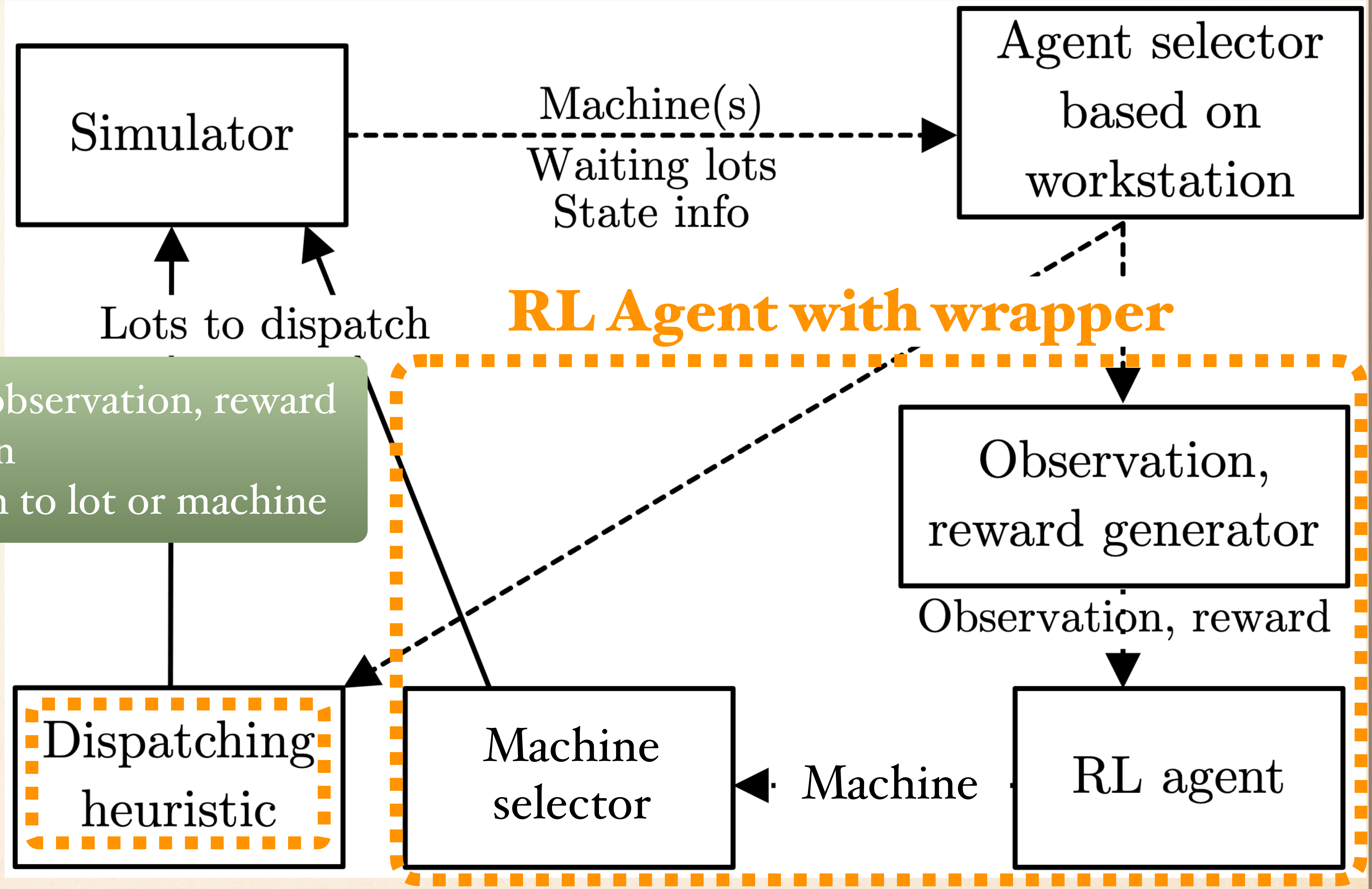
RL framework

6. Select agent (RL / heuristic)
7. Find lot or machine based on agent

Sim

8. Execute selection

1. Generate observation, reward
2. Pick Action
3. Map action to lot or machine



Action spaces

- 2 decision points
  - lot available => assign to machine
  - machine available => find lot
- 4 available action spaces
  - direct lot / machine selection
  - queue creation
  - heuristic selection

Actions

Pick operation for available machine[1]
Assign lot to machine's queue[2]
Pick lot from for available machine[3]
Select heuristic for available machine[4]

Observation Space

- Construct observation space from pre-defined features
    - single / multi features
    - some limited to specific action space
- Define own features based on custom data collection (plugins)

Observation space components

Machine	Global	Operation type / Lot
Next maintenance[1234]	No of WIP lots[1234]	Available lot count for op.[1234]
Setup/processing ratio[1234]	Average utilization[1234]	Maximum batch size[1234]
Idle/utilized ratio[1234]	No of lot types / routes[1234]	Batch utilization[1234]
Class (batch/cascade/...)[1234]		Steps remaining after op.[1234]
Cost of current setup[1234]		Lot timeliness[1234]
Bottleneck factor[1234]		Lot idle time[1234]
Queue length[2]		Lot priority[1234]
Machine family size[1234]		Processing time[1234]
Count of possible setups[1234]		Fit before maintenance[1234]
Time of setups[1234]		Setup time[1234]
Count of op. types[1234]		Rel. machine performance[1234]
		Remaining coupling time[1234]

Reward Function

- Define scalar function using pre-defined reward components
    - Sparse and dense functions
- Add custom components based on data collection plugins

Reward components

Dense	Sparse
Timeliness of lots	Lot completion
No of WIP lots	Coupling violation
Utilization	

Summary: Observation & Action Spaces, Reward

Actions

Pick operation for available machine[1]
Assign lot to machine's queue[2]
Pick lot from for available machine[3]
Select heuristic for available machine[4]

Reward components

Dense

Timeliness of lots
No of WIP lots
Utilization

Sparse

Lot completion
Coupling violation

Observation space components

Machine

Next maintenance[1234]
Setup/processing ratio[1234]
Idle/utilized ratio[1234]
Class (batch/cascade/...)[1234]
Cost of current setup[1234]
Bottleneck factor[1234]
Queue length[2]
Machine family size[1234]
Count of possible setups[1234]
Time of setups[1234]
Count of op. types[1234]

Global

No of WIP lots[1234]
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No of lot types / routes[1234]

Operation type / Lot

Available lot count for op.[1234]
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Lot priority[1234]
Processing time[1234]
Fit before maintenance[1234]
Setup time[1234]
Rel. machine performance[1234]
Remaining coupling time[1234]

Instantiation of Environments

```python
from rl.env.action_choose_rule_for_machine import ChooseRuleForMachine
from rl.env.actions import SingleObservationFeature
from rl.env.agent import RLAgent, GreedyAgent
from rl.env.environment import DynamicSCFabSimEnv
from rl.env.reward import Reward
from simulation.plugins.wandb_plugin import WandBPlugin

R = Reward
O2 = ChooseRuleForMachine.Observation
P = GreedyAgent.Policy
DEMO_ENV_2 = lambda max_steps=100000000, max_days=730: DynamicSCFabSimEnv(
    action=ChooseRuleForMachine(
        alternatives=[P.CriticalRatio, P.FIFODeadline, P.FIFOWaiting, P.AvoidSetup, P.HotLotFirst, P.CombinedFIFO, ],
        observation_space=[O2.Machine.cascading, O2.Machine.bottleneck_factor, O2.Machine.setup_last_at,
                           O2.Machine.setup_last_cost, O2.Machine.idle_processing_ratio, O2.Machine.next_maintenance,
                           SingleObservationFeature(lambda instance, **kwargs: len(instance.done_lots), True), ], ),
    agents=[
        RLAgent(idx=0, machine_groups=['Diffusion']), RLAgent(idx=1, machine_families=['DefMet_BE_33', 'DefMet_BE_42']),
        GreedyAgent(policy=GreedyAgent.Policy.CombinedCR),
    ],
    simulator_params=dict(plugins=[WandBPlugin()], run_to=3600 * 24 * max_days, ), dataset='SMT2020_LVHM',
    reward=5 * R.Dense.LotWipCount() + R.Dense.LotTimeliness() + 20 * R.Sparse.LotCompletion(), max_steps=max_steps, )
```

Future Work

- Development of optimised RL agents for the environment
- Analyse adaptivity of agents to evolving factories
- Integration of datasets with physical fabs, transfer learning from current dataset to industrial ones

Time for Questions

Thank You for Your Attention

Download PySCFabSim at
https://github.com/prosysscience/PySCFabSim-release

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(2) B. Kovács, P. Tassel, R. Ali, M. El-Kholany, M. Gebser and G. Seidel, "A Customizable Simulator for Artificial Intelligence Research to Schedule Semiconductor Fabs," *2022 33rd Annual SEMI Advanced Semiconductor Manufacturing Conference (ASMC)*, 2022, pp. 1-6, doi: 10.1109/ASMC54647.2022.9792520.