ARCHITECTURE FOR **DIGITAL TWIN**-BASED **REINFORCEMENT LEARNING OPTIMIZATION** OF **CYBER-PHYSICAL SYSTEMS**

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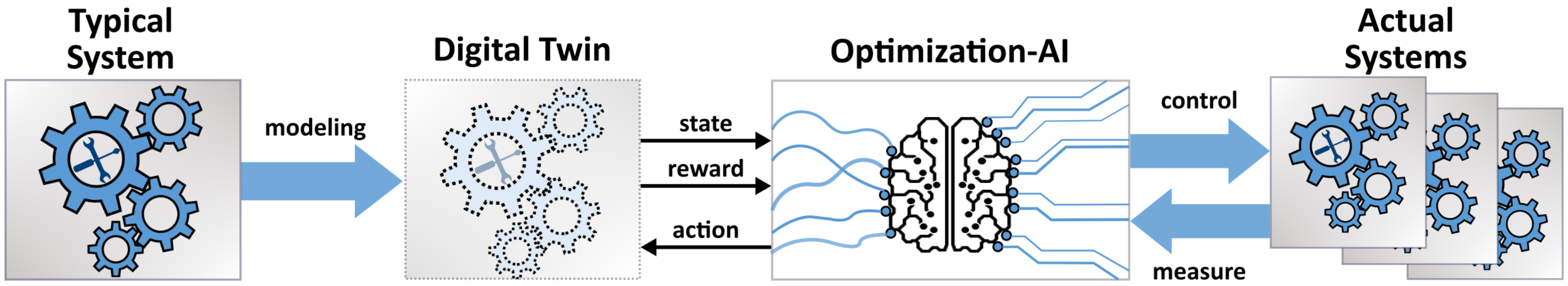
Introduction

- Calibration and optimization of industrial CPS in high demand
- AI-controlled optimization = attractive solution -> lack of training data!
- Possible solution:
  - Simulation-based training data generation -> Digital Twin!

How does an architecture look like that leverages Reinforcement Learning (RL) training using Digital Twins (DT)?

Phases



We consider three phases:

1. **Training phase**
   - Training of generic RL agent
   - Varying digital models -> reduce overfitting
2. **Operational phase**
   - Deployment of RL agent instance
   - Gathering data
3. **Fine-Tuning phase**
   - Fine-tuning using data and DT from 2
   - Improvement of generic RL agent

Literature

	[1] [2]	[3]	[4]	[5]	[6]
Sim.-based ML-Training	x	x	x	x	
Usage of DTs		x		x	x
Architectural considerations		x	x		
Post-deployment learning					x

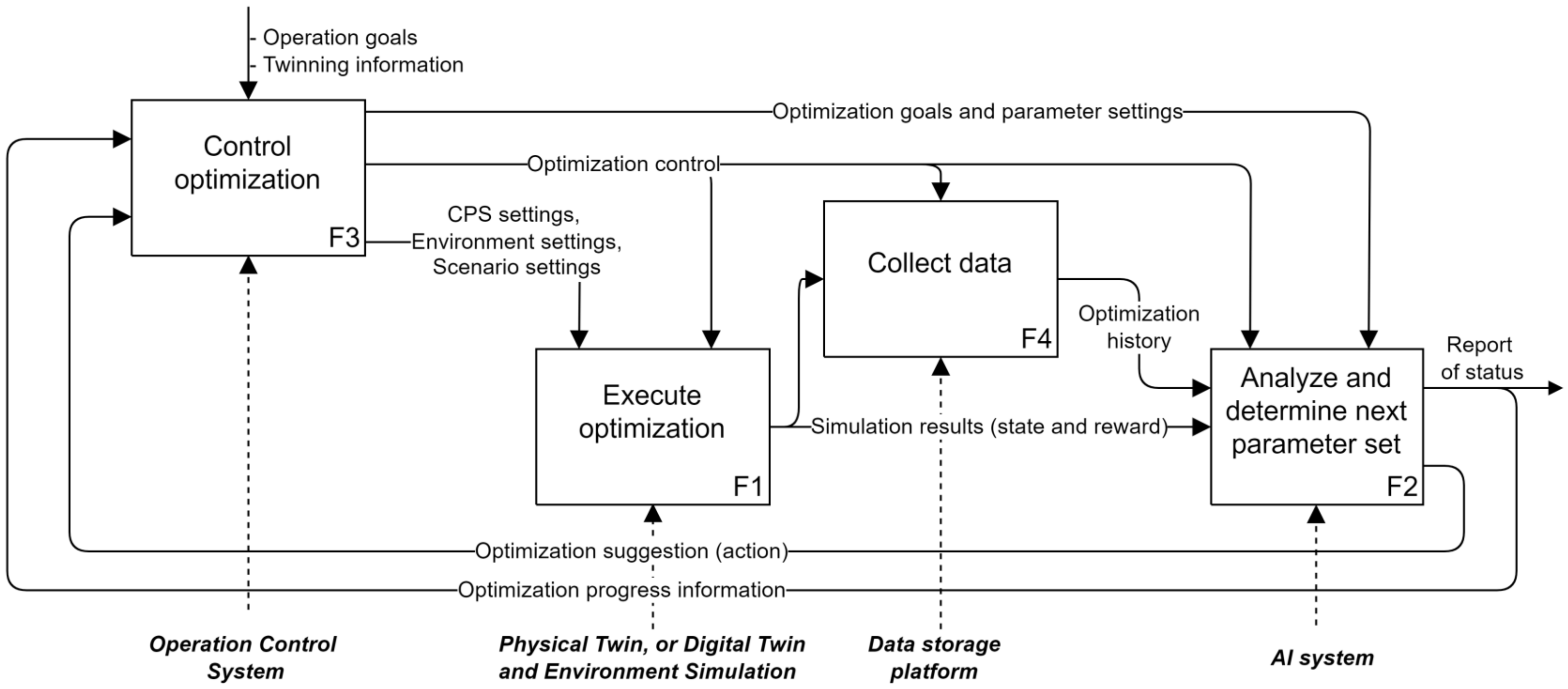
Requirement view

- Requirements originate from RL requirements and multi-phase application

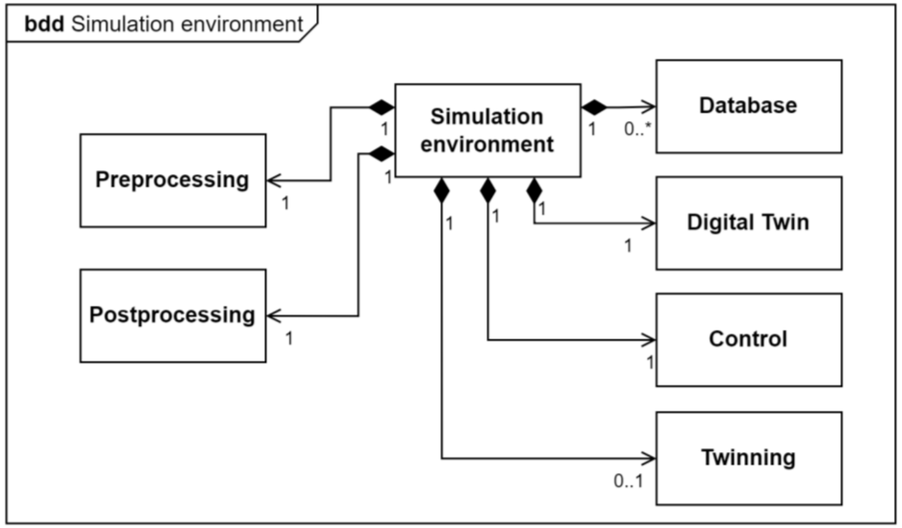
1. Accuracy - Accuracy needed depends on application and algorithm
2. Calculation time - Calculation time must minimized

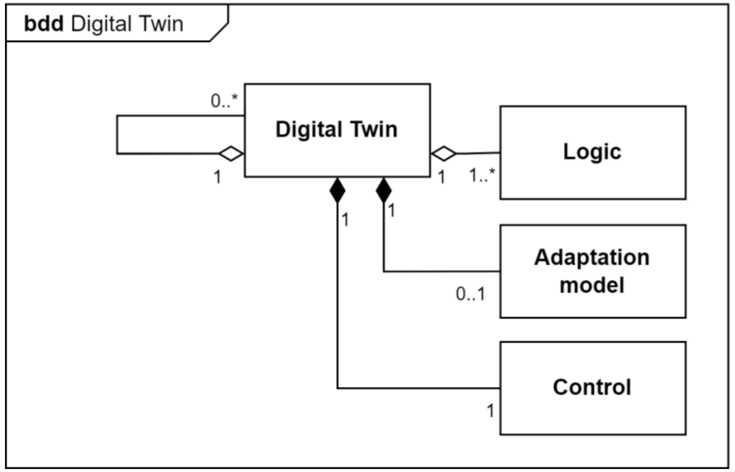
3. Reusability – Re-usage of models during phases
4. Maintainability – Design for the possiblity of containerization
5. Integrability – Enable IP Protection

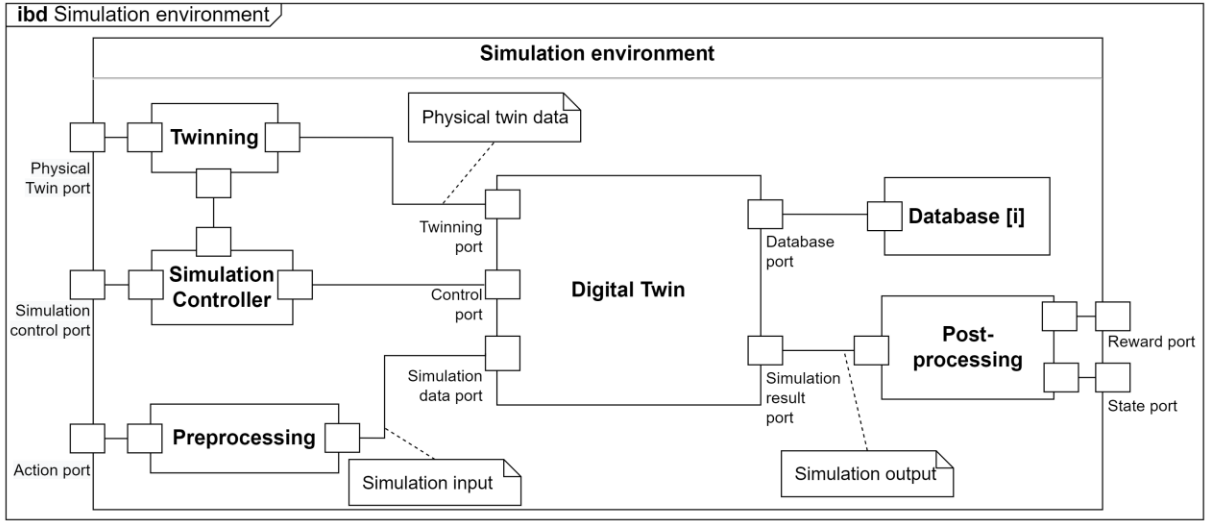
Functional view

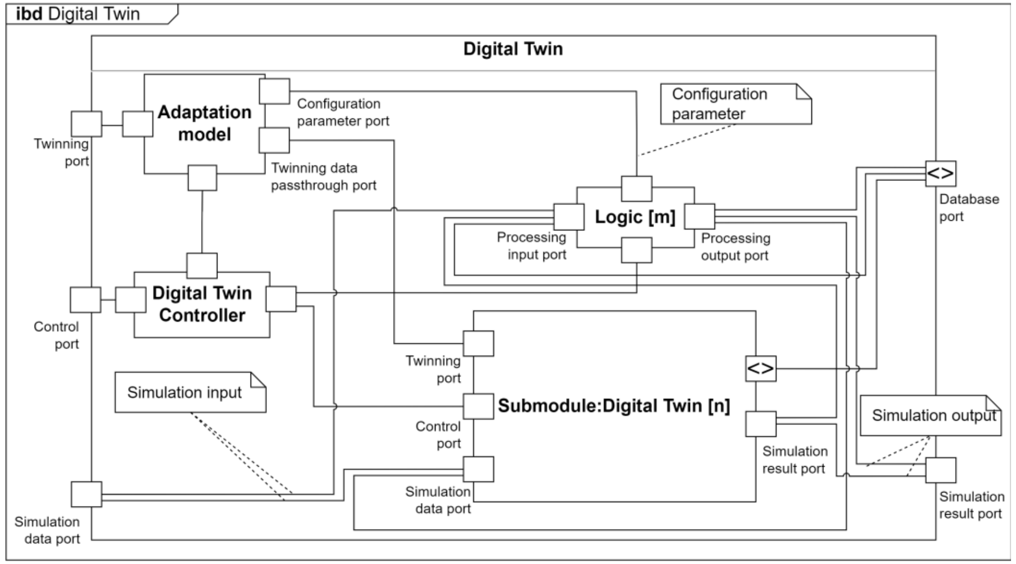


Logical view









Technical view

- No specific implementation technologies required
- Architecture enables co-simulation frameworks (e.g., FMI)

- Focus on:
  - Integrability
  - Reusability
  - Maintainability

- In depth evaluation of technical considerations has not be finalized yet.
  - Integration of standards

Final Words

- Presented an architecture
  - Combining RL and DT
  - Distinguished 3 phases
  - 4 architectural views

- Development is still work in progress
  - Improve consistency between views
  - Increase level of detail
  - Improve technical view
  - Further validation of solution

Any questions, suggestions and points of improvement?

Imprint

Topic: **Presentation at TwinArch workshop at ECSA2023**

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Sources:

[1] Degrave et al.: Magnetic control of tokamak plasmas through deep reinforcement learning. Nature 602(7897), 414–419 (2022).

[2] Osiński et al.: Simulation-based reinforcement learning for real-world autonomous driving. In: 2020 IEEE International Conference on Robotics and Automation (ICRA), pp. 6411–6418. IEEE (2020)

[3] : Alexopoulos et al.: Digital twin-driven supervised machine learning for the development of artificial intelligence applications in manufacturing. Int. J. Comput. Integr. Manuf. 33(5), 429–439 (2020).

[4] Ju et al.: Transferring policy of deep reinforcement learning from simulation to reality for robotics. Nature Machine Intelligence 4(12), 1077–1087 (2022).

[5] Shen et al: Deep reinforcement learning for flocking motion of multi-uav systems: Learn from a digital twin . IEEE Internet of Things Journal 9(13), 11141–11153 (2021)

[6] Sun et al.: Adaptive federated learning and digital twin for industrial internet of things. IEEE Transactions on Industrial Informatics 17(8), 5605–5614 (2021).