







## Project Type

- Master Thesis
- Bachelor Thesis
- Research Project

## Supervisors

-  Niklas Freymuth
-  niklas.freymuth@kit.edu
-  Philipp Becker
-  philipp.becker@kit.edu
-  Tai Hoang
-  tai.hoang@kit.edu

## Difficulty

Algorithmic



Math



Application



# Graph Network Simulators are Sample Efficient World Models

## Description

Accurate simulation of physical systems is crucial for many engineering disciplines. Yet, classical simulators are often prohibitively expensive for complex simulations, requiring hours or even days to produce accurate results. In robotics, deep Reinforcement Learning (RL) has become a popular tool for developing capable agents for difficult tasks. Yet, training RL agents requires large amounts of data. For tasks such as the manipulation of deformable objects, the cost of running simulation does makes training infeasible.

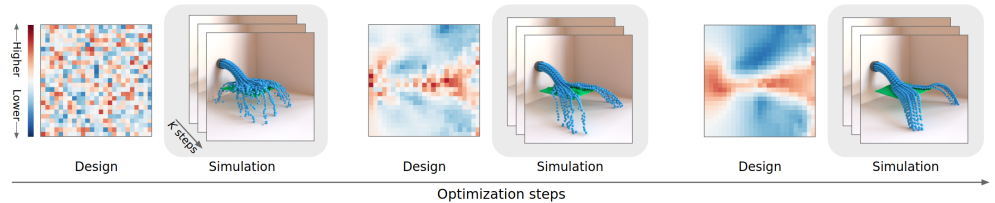


Figure 1: A simulated stream of water (blue) collides with a deformable plate (green). The plate consists of individual pixels with different height (heatmaps) that can be adapted by a learned agent. Solving the inverse design problem means finding a configuration of pixel heights such that the water stream splits into two "pools" on the left and right of the plate (right figure).

Recently, data-driven general-purpose Graph Network Simulators (GNS) [1] have become a popular tool for simulation, as they offer accurate, fast and differentiable predictions. They provide stable rollouts and suitable gradients over multiple hundred simulation steps, and have thus been used to optimize simple inverse design problems, as shown in Figure 1 [2].

In this work, we want to extend research on GNS for inverse problems towards RL. Motivated by recent advances that show that transformers are efficient world models [3], we want to use GNS for model-based RL to solve complex robotic manipulation tasks without the need for large amounts slow and cumbersome classical simulations. A core challenge of this thesis is the potential model error of the GNS, which may require robust RL optimization or fine-tuning the model when the simulation becomes inaccurate for newly explored choices of the RL agent.

## Tasks

- Literature Review: Get familiar with Graph Network Simulators and Model-based Reinforcement Learning.
- Algorithm Design: Integrate a learned Graph Network Simulator into a Model-based RL framework and make the optimization robust.
- Evaluation: Evaluate your algorithm on different deformable object simulations that require an RL agent to interact with the learned model.

## References

- [1] Tobias Pfaff, Meire Fortunato, Alvaro Sanchez-Gonzalez, and Peter Battaglia. Learning mesh-based simulation with graph networks. In *International Conference on Learning Representations*, 2020.
- [2] Kelsey Allen, Tatiana Lopez-Guevara, Kimberly L Stachenfeld, Alvaro Sanchez Gonzalez, Peter Battaglia, Jessica B Hamrick, and Tobias Pfaff. Inverse design for fluid-structure interactions using graph network simulators. *Advances in Neural Information Processing Systems*, 35:13759–13774, 2022.
- [3] Vincent Micheli, Eloi Alonso, and François Fleuret. Transformers are sample-efficient world models. In *The Eleventh International Conference on Learning Representations*, 2022.