1. Hybrid Symbolic-Generative AI Physics Informed Neural Networks for Generating First Principal Physics Based Simulations

Real-time physics models are used for simulating test conditions that cannot be conducted physically. While creating simplified 1D models is generally straightforward, replicating complex system dynamics such as fluid inertance and compressibility effects requires understanding where to apply simplifications that retain physical validity. This project investigates how deep neural networks can perform automated mathematical derivation when starting from a set of governing equations, applying systematic simplification steps and assumptions, to end with a generated simplified equation as executable Python code. The goal is to understand what deep networks do when applying logic, rules of thumb, and other typical processes used by modern engineers in the field. Initial investigations will focus on simple physics such as balloon inflation dynamics or similar, encompassing model generation through symbolic derivation, network training, interpretability of derivation steps, and visualization of the mathematical reasoning process.

2. Topics Numero Due