Project Proposal

Physics-Informed Neural Networks for Modeling of Radial Compressor Losses

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General Information

Type:	Master Thesis (30 ECTS)
Laboratory:	Laboratory for Applied Mechanical Design (LAMD)
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Background

Supercritical power cycles are expected to play a pivotal role in the energy transition due to their potential for higher thermal efficiencies and compact designs. In these cycles, compressors operate with supercritical fluids—working fluids at pressures and temperatures beyond their critical point—where the ideal gas law fails to describe the real fluid behavior. Supercritical fluids exhibit strong real-gas effects, highly non-linear thermo-physical properties, and thin boundary layers, all of which complicate the accurate prediction of aerodynamic losses in radial compressors.

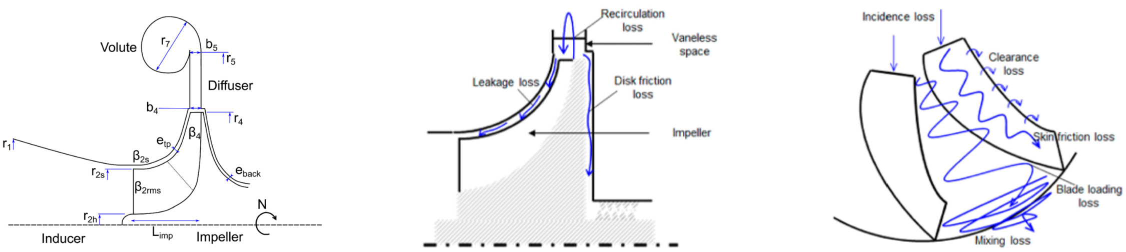

Figure 1: 1D compressor–turbine geometry with associated aerodynamic loss mechanisms.

Figure 1 shows a 1D schematic with the associated aerodynamic losses required to model compressor performance. Currently, aerodynamic losses are typically estimated using empirical correlations. These correlations were derived from experimental data on compressors operating under subcritical conditions, where property variations are smoother and boundary layers constitute a smaller fraction of the total flow. The aim of this project is not to replace or extend these empirical correlations directly, but to develop a novel pipeline for predicting aerodynamic losses using machine learning techniques—specifically, Physics-Informed Neural Networks (PINNs) [Raissi et al., 2019].

Proposed Approach

The central idea of this project is to use empirical correlations as a training baseline, while employing Physics-Informed Neural Networks to construct a surrogate model that embeds thermodynamic laws and governing equations directly into the learning process. This approach enables the creation of a physics-consistent model that not only reproduces the trends of empirical correlations but also has the flexibility to generalize across different operating conditions.
PINNs differ from conventional neural networks by incorporating conservation laws and differential equations into their loss function [Cuomo et al., 2022], ensuring that predictions respect physical constraints. Their use in this context is motivated by three advantages:

1. They provide a framework for integrating sparse or synthetic data with fundamental physics.

2. They offer scalability and computational efficiency, accelerating simulations by orders of magnitude compared to high-fidelity CFD.
3. They establish a reusable pipeline for surrogate loss modeling, which can be extended to future datasets, including experimental or CFD-based data.

The contribution of this thesis is therefore methodological: demonstrating how PINNs can be trained on existing empirical loss data to establish a robust, physics-informed surrogate modeling pipeline for supercritical compressors. Importantly, the 1D model used to obtain aerodynamic losses and predict compressor performance is already available and does not require development within this project.

Objective

A validated Physics-Informed Neural Network (PINN) framework capable of accurately predicting aerodynamic losses in a supercritical radial compressor, using empirical correlations as a baseline reference.

Tasks

1. Conduct a literature review of neural-network-based loss modeling in compressors and existing applications of PINNs in thermofluid systems.

2. Identify and implement an appropriate data sampling and preprocessing strategy based on empirical loss correlations.

3. Develop a PINN architecture embedding the relevant governing thermodynamic and fluid-dynamic equations.

4. Train and validate the PINN against baseline empirical correlations, assessing performance, generalization, and computational efficiency.

5. Document results and discuss implications for extending the methodology to CFD- or experiment-based datasets in future work.

NB: The scope and tasks may be refined depending on progress, results, and available resources.

Prerequisite Knowledge

1. Fundamentals of machine learning and neural network architectures.
2. Programming skills (MATLAB / Python).
3. Basic understanding of thermodynamics and fluid mechanics (helpful but not strictly required).

No explicit prior knowledge of turbomachinery is required; the project is focused primarily on the development of the machine learning pipeline.

References

Salvatore Cuomo, Vincenzo Schiano Di Cola, Fabio Giampaolo, Gianluigi Rozza, Maziar Raissi, and Francesco Piccialli. Scientific machine learning through physics-informed neural networks: Where we are and what's next. *CoRR*, abs/2201.05624, 2022. URL https://arxiv.org/abs/2201.05624.

M. Raissi, P. Perdikaris, and G.E. Karniadakis. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics*, 378:686–707, 2019. ISSN 0021-9991. doi: https://doi.org/10.1016/j.jcp.2018.10.045. URL https://www.sciencedirect.com/science/article/pii/S0021999118307125.