Spectral POD and autoencoders for compression and prediction of vortex rope – 30 ECTS

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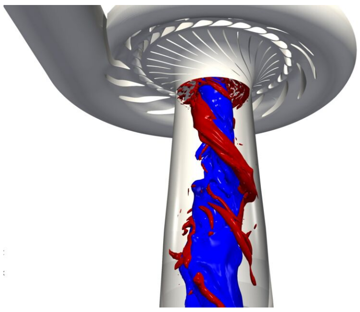
About the job

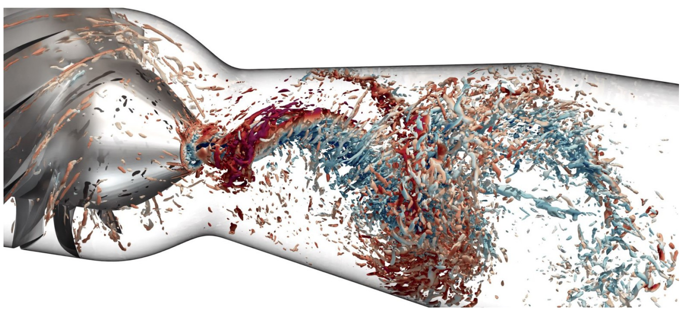
Explore the cutting edge at the intersection of Artificial Intelligence (AI) and fluid flows by performing your thesis with us. We aim to advance data-driven analysis of complex hydrodynamic instabilities in hydraulic turbines using state-of-the-art machine learning As a thesis worker at the Division of Applied Thermodynamics and Fluid Mechanics, you will benefit from active knowledge exchange and contribute to our research environment. All thesis projects include a local room and necessary resources and are supported by an experienced supervisor throughout the project.

Background

The decelerating swirling flow in the draft tube of hydraulic turbines at part-load conditions can lead to a self-induced instability known as the vortex rope. This instability generates pressure pulsations that reduce efficiency and may cause harmful vibrations in hydropower systems. A detailed understanding and the ability to predict the temporal evolution of such flows are crucial for control and for the safe and flexible operation of hydraulic turbines. Fig. 1 shows two examples of this instability in hydraulic machines.



(a) Francis 99 model turbine [1]

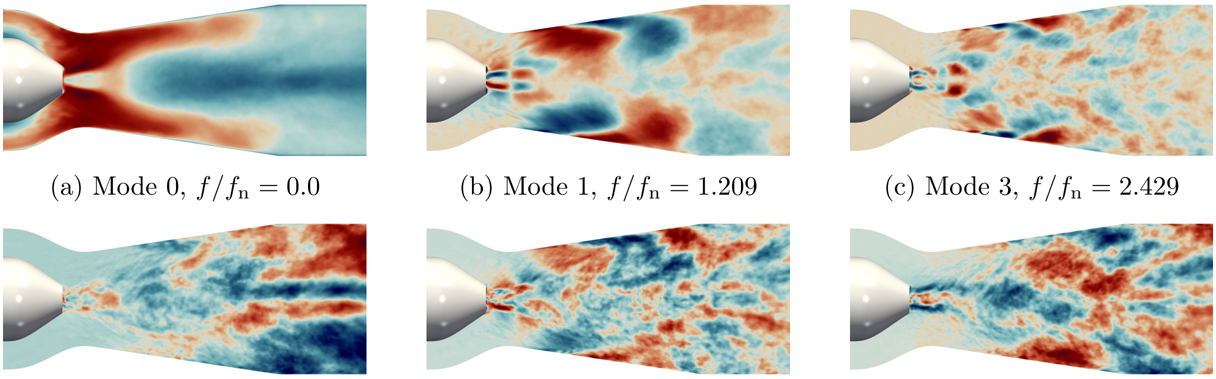


(b) Timisoara Swirl Generator [2]

Figure 1: Illustration of vortex rope in (a) a Francis turbine and (b) a swirl generator.

Model order reduction (ROM) techniques play a key role in extracting dominant structures from fluid flows and in revealing the underlying physics of complex dynamics. They reduce the dimensionality of a system without significant loss of information and provide efficient low-dimensional representations for analysis and prediction. Among the most widely used methods are Proper Orthogonal Decomposition (POD) [3, 4] and Dynamic Mode Decomposition (DMD) [5], which have been applied to many fluid-mechanics problems to identify coherent flow structures and their temporal evolution.

In a recent study, we performed an extensive modal analysis of the vortex rope in the Timisoara Swirl Generator (TSG) model using DMD [2]. High-fidelity computational fluid dynamics (CFD) data were obtained with an improved delayed detached eddy simulation of the TSG, a laboratory model designed to reproduce flow instabilities similar to those occurring in hydraulic turbines at part-load conditions. The DMD analysis identified coherent structures at distinct frequencies and revealed the complex interaction of different physical phenomena (Fig. 2). While DMD provides valuable physical insight, its predictive capability remains limited for strongly turbulent, broadband flows.



(a) Mode 0, $f/f_\mathrm{n} = 0.0$ (b) Mode 1, $f/f_\mathrm{n} = 1.209$ (c) Mode 3, $f/f_\mathrm{n} = 2.429$

(d) Mode 5, $f/f_\mathrm{n} = 0.525$ (e) Mode 7, $f/f_\mathrm{n} = 1.295$ (f) Mode 9, $f/f_\mathrm{n} = 0.648$

Figure 2: Real part of the first 6 DMD modes of the TSG model

Spectral Proper Orthogonal Decomposition (SPOD) [6] provides a natural next step for analyzing broadband turbulent flows such as the vortex rope. SPOD can be viewed as the frequency-domain form of POD, and is closely related to DMD. In fact, SPOD modes can be interpreted as optimally averaged DMD modes obtained from an ensemble DMD problem. These properties make SPOD particularly suitable for extracting energetically significant, frequency-resolved coherent structures and for providing a robust basis for data-driven reduced-order models and flow prediction.

While POD, DMD, and SPOD are powerful tools for extracting coherent structures and for model reduction, they remain intrinsically linear. They represent the flow dynamics by projecting high-dimensional data onto a linear subspace and may therefore miss essential nonlinear interactions characteristic of turbulent flows. These limitations motivate the use of nonlinear machine-learning techniques, such as autoencoders [7], self-supervised networks trained to reproduce their input and capable of identifying curved, low-dimensional manifolds beyond the reach of linear projections. Convolutional neural networks (CNNs) are particularly well suited for the encoder and decoder of an autoencoder, enabling efficient compression and faithful reconstruction. Figure 3 presents a schematic of a Convolutional Autoencoder (CNN–AE) that can be used for nonlinear compression and prediction of vortex rope dynamics.

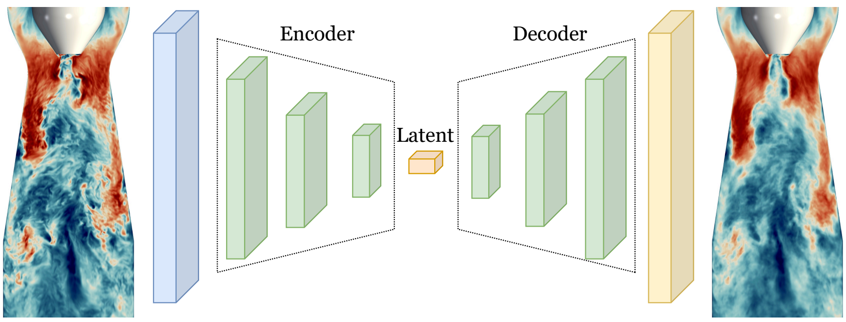


Figure 3: Schematic of a CNN–AE for nonlinear compression of vortex rope dynamics.

Scope

This thesis will investigate data-driven reduced-order modeling and prediction of vortex rope dynamics using Spectral Proper Orthogonal Decomposition (SPOD) and convolutional autoencoders (CNN–AEs). High-fidelity CFD data of the Timisoara Swirl Generator (TSG), previously generated with resolved simulations in OpenFOAM, will be used as the data source, and no new CFD simulations are required unless additional data are deemed necessary.

The first part of the project will apply SPOD to extract energetically significant, frequency-resolved coherent structures and to identify the dominant temporal dynamics of the vortex rope. Next, a CNN–AE architecture will be designed and trained to compress the high-dimensional flow fields into a compact latent representation. If time allows, the thesis will also explore modeling the temporal dynamics of the latent variables to predict the short-term evolution of the flow.

The work will be carried out entirely in Python using established scientific and machine-learning libraries (e.g. NumPy, PyTorch). All codes, processing scripts, and trained models will be released in a public open-source repository to ensure full reproducibility and to support future research.

The project will address the following research questions.

- How effectively can SPOD extract and rank frequency-resolved coherent structures in the vortex rope?
- Can a CNN–AE provide accurate low-dimensional representations of the flow field?
- How do the modal structures and predictive capabilities of DMD and SPOD compare to the non-linear compression of CNN–AE?

The scope is designed for a 30 ECTS master's thesis and ensures feasibility by relying on existing high-fidelity CFD data while providing new insights into nonlinear reduced-order modeling and flow-field prediction.

General methodology

The project will follow a structured workflow consisting of the following main stages.

1. **Project initiation**

   1.1 Review recent literature on reduced-order modeling and prediction of turbulent flows, particularly SPOD and autoencoders.

   1.2 Establish a project plan with milestones and deliverables.

2. **Data preparation and familiarization**

   2.1 Review and understand the available high-fidelity CFD dataset of the Timisoara Swirl Generator (TSG), including spatial and temporal resolution, file formats, and preprocessing requirements.

   2.2 Develop Python routines to load, handle, and visualize the data efficiently.

3. **SPOD analysis**

   3.1 Implement or adapt an SPOD algorithm to extract frequency-resolved coherent structures from the CFD dataset.

   3.2 Identify and rank the most energetic modes and analyze their temporal dynamics.

   3.3 Compare key SPOD modes with previously obtained DMD modes to highlight similarities and differences.

4. **CNN–AE modeling**

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4.1 Preprocess the CFD data as needed to make it suitable for CNN–AE training.

4.2 Design and train a CNN–AE to compress the high-dimensional flow fields into a compact latent representation.

4.3 Evaluate reconstruction accuracy and compression efficiency.

4.4 If time allows, develop a latent-space dynamics model to forecast the short-term evolution of the flow.

5. **Analysis and documentation**

5.1 Assess how effectively SPOD and CNN–AE capture the dominant coherent structures and predict the future flow states.

5.2 Compare the predictive capabilities of SPOD-based and DMD-based reduced-order models.

5.3 Document all methods, results, and conclusions in the thesis report.

5.4 Prepare and release all codes, processing scripts, and trained models in a public open-source repository to ensure reproducibility and support future research.

What you'll bring

You are pursuing a Master of Science degree in Mechanical Engineering, Aeronautical Engineering, Energy–Environment–Management, or a related field at Linköping University, and have a solid background in fluid mechanics, numerical methods, programming, and CFD. You also have strong analytical and communication skills and work well in a team.

Meriting experience

The following qualifications are considered meriting.

- Previous experience with open-source CFD, such as OpenFOAM.
- Courses or prior experience in machine learning.
- Familiarity with deep learning frameworks such as PyTorch or TensorFlow.
- Skills in Python programming and numerical libraries (e.g., NumPy, Matplotlib).
- Experience with visualization and data analysis in Python.
- Experience with Linux environments and high-performance computing.
- Experience with scientific writing in LaTeX.

Other details

- **Location:** It is necessary that you pursue your thesis at Linköping University.
- **Duration:** The duration of the thesis is 20 weeks (30 ECTS credits), starting in Jan. 2025.
- **Number of students:** Ideal for two students but can be adapted for one student.
- **Application period:** Reviewed on a rolling basis until the position is filled.

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