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UNIVERSITY OF TECHNOLOGY

# Computational fluid dynamics and machine learning for flexible and sustainable hydropower

Håkan Nilsson

SVC R&D days 2023-02-23

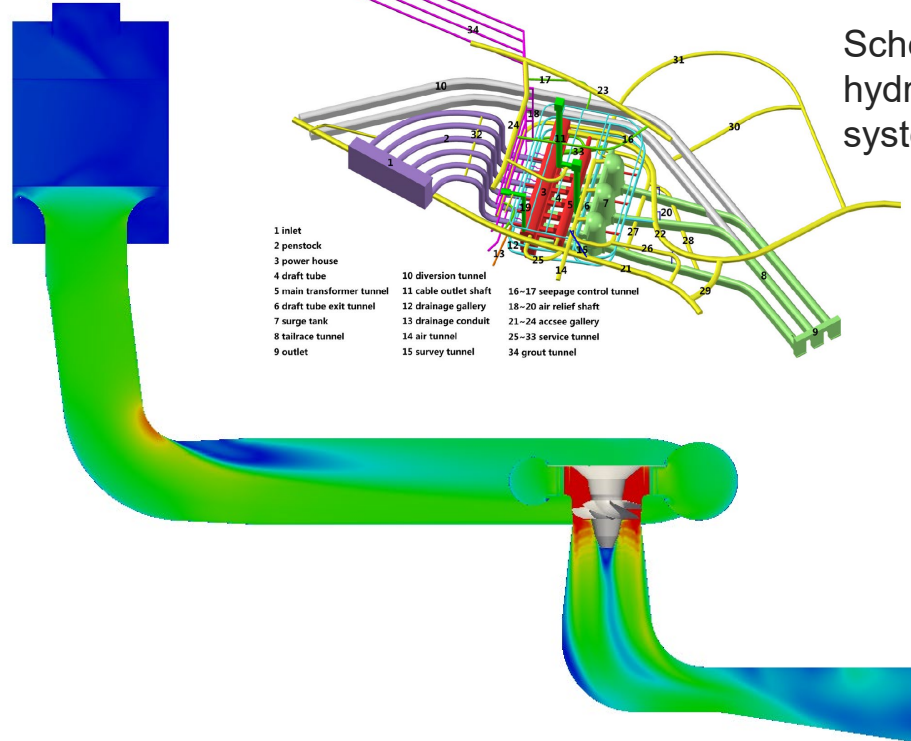
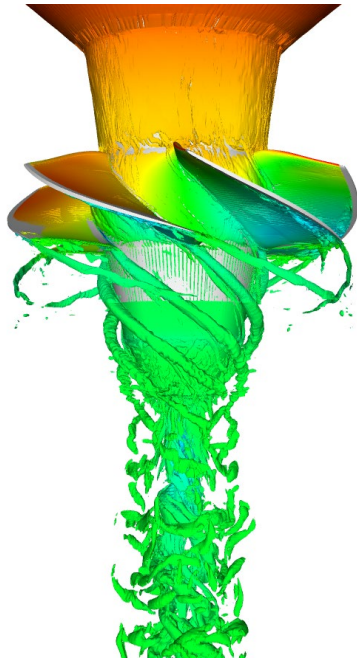
Department of Mechanics and Maritime Sciences

Division of Fluid Dynamics

Chalmers University of Technology

# The hydropower research area (for me)

- fluid dynamics: from details to system dynamics, transient operation and cavitation
- development of methods for numerical simulations of fluid flow

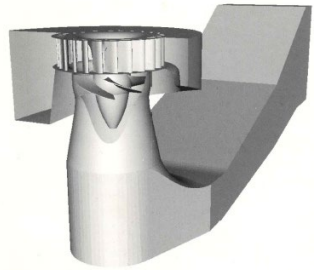


# Development of CFD for hydraulic turbines

## PhD theses, 2002, 2008, 2012 and 2016



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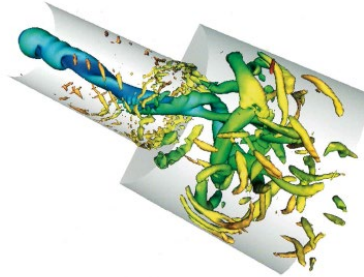


Numerical Investigations of  
Turbulent Flow in Water Turbines

HÅKAN NILSSON

*Department of Thermo and Fluid Dynamics*  
CHALMERS UNIVERSITY OF TECHNOLOGY  
Gothenburg, Sweden 2002

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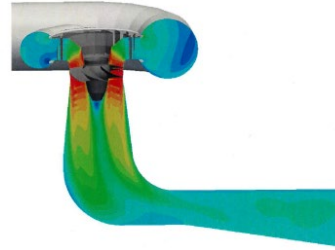


Analytical and Numerical Studies  
of Internal Swirling Flows

WALTER GYLLENRAM

*Division of Fluid Dynamics*  
*Department of Applied Mechanics*  
CHALMERS UNIVERSITY OF TECHNOLOGY  
Gothenburg, Sweden 2008

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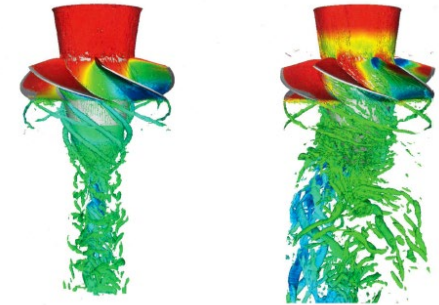


Towards Full Predictions of the Unsteady  
Incompressible Flow in Rotating Machine  
Using OpenFOAM

OLIVIER PETIT

*Department of Applied Mechanics*  
*Division of Fluid Dynamics*  
CHALMERS UNIVERSITY OF TECHNOLOGY  
Gothenburg, Sweden 2012

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Turbulence-resolving Simulations  
of Swirling Flows

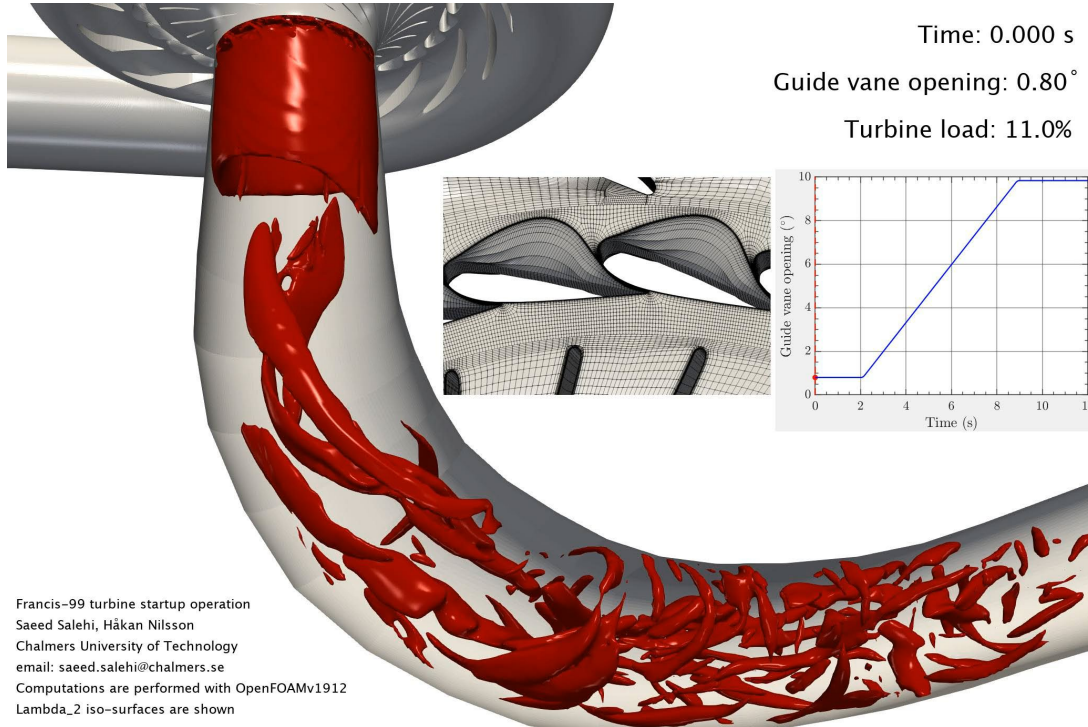
ARDALAN JAVADI

*Department of Applied Mechanics*  
*Division of Fluid Dynamics*  
CHALMERS UNIVERSITY OF TECHNOLOGY  
Gothenburg, Sweden 2016

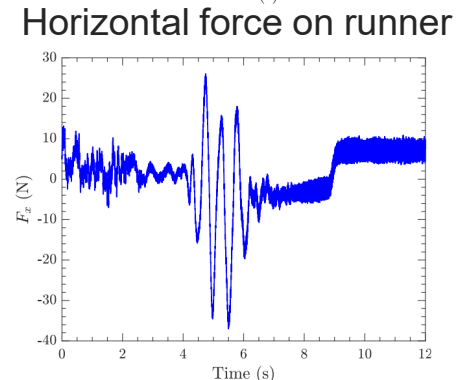
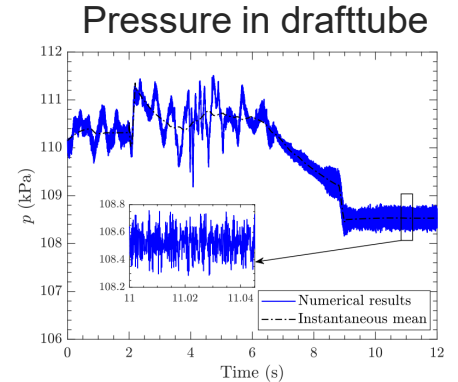
# Development of CFD for hydraulic turbines

## Post-doc Saeed Salehi, 2019-2022

Start-up to BEP, Francis-99 *Renewable Energy*. Vol. 188, p. 1166-1183  
(shut-down in *Renewable Energy*. Vol. 179, p. 2322-2347 and *OpenFOAM Journal*. Vol. 1, p. 47-61)



Francis-99 turbine startup operation  
Saeed Salehi, Håkan Nilsson  
Chalmers University of Technology  
email: saeed.salehi@chalmers.se  
Computations are performed with OpenFOAMv1912  
Lambda\_2 iso-surfaces are shown

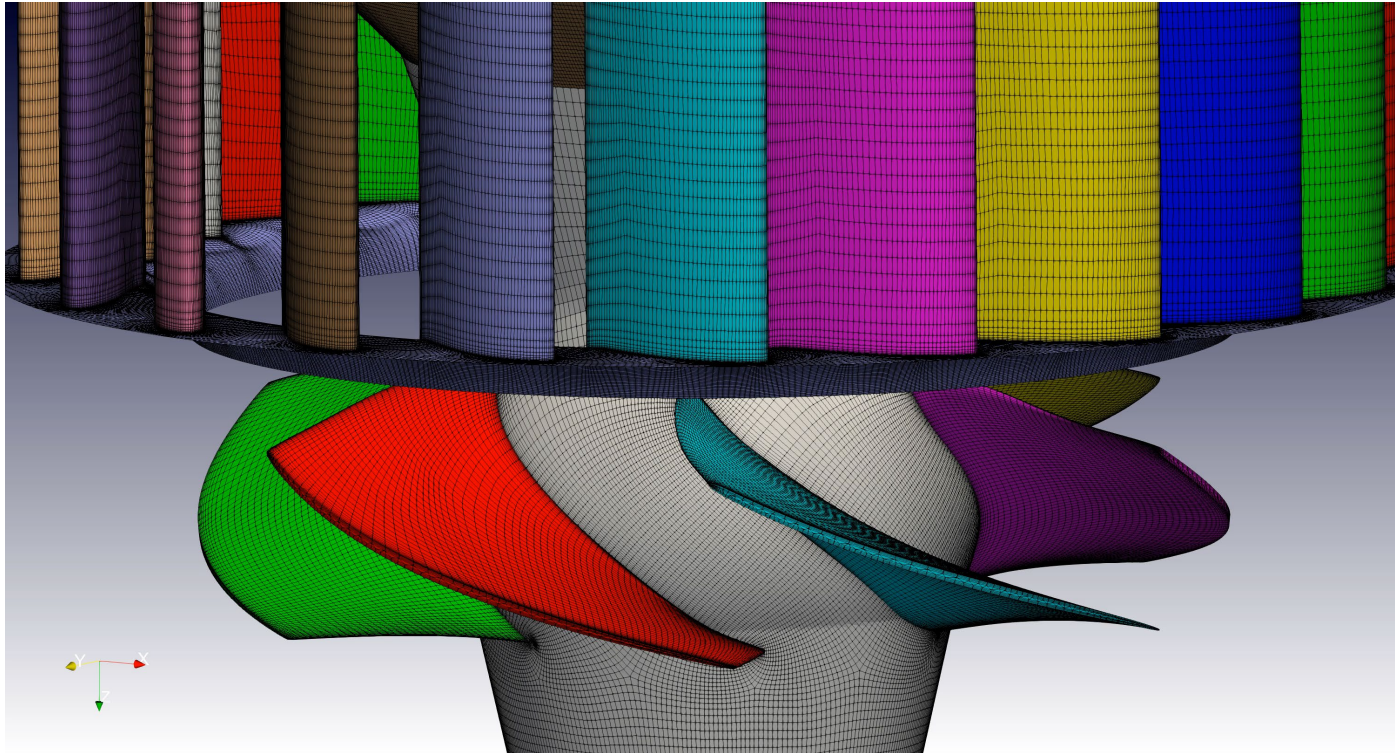




# Development of CFD for hydraulic turbines

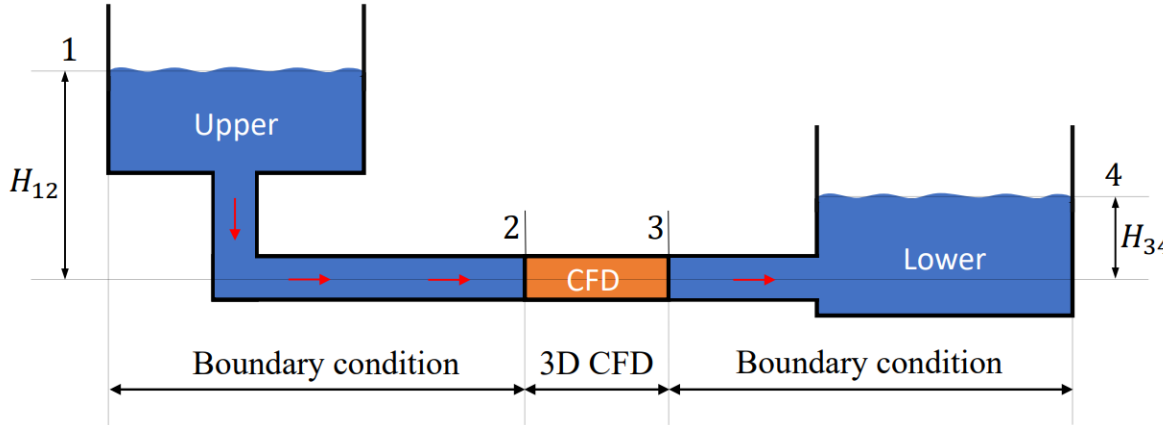
## Post-doc Saeed Salehi, 2019-2022

Kaplan turbine transients *Computer Physics Communications*, Volume 287, 2023

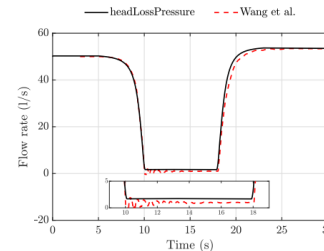
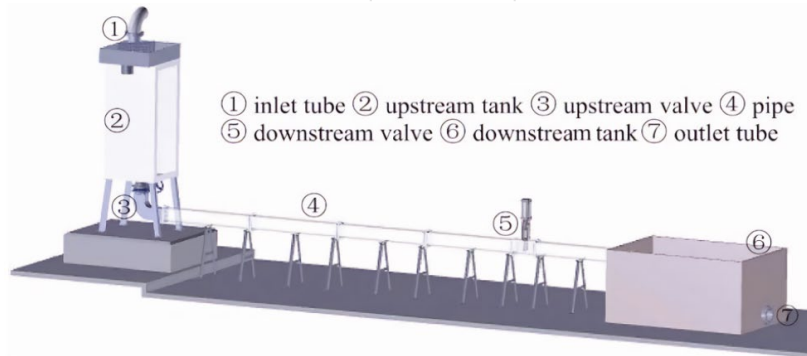


# Development of CFD for hydraulic turbines

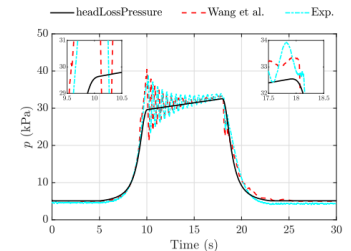
A head loss pressure boundary condition for hydraulic systems, Fahlbeck et al., OpenFOAM Journal. Vol. 2, p. 1-12



Variable	Description
pFar	Kinematic pressure far from patch, $p_{Far}^*$
HFar	Elevation far from patch, $H_{Far}$
dP	Hydraulic diameter of patch, $d_{h,p}$
minorLossFactors	Minor loss factors: $(d_{h,1}^{\dagger}, k^{\dagger\dagger}, name^{\dagger\dagger})$
frictionLossFactors	Friction loss factors: $(d_{h,1}^{\dagger}, \epsilon^{\dagger}, L^{\dagger}, name^{\dagger\dagger})$
kDynamic	Dynamic minor loss coefficient, $k$
dkDynamic <sup>†</sup>	Hydraulic diameter of kDynamic, $d_{h,1}^{\dagger}$
flowRate	Flow rate to the reservoir, $Q_r$
Ar <sup>†</sup>	Reservoir surface area, $A_r$
dFar <sup>§</sup>	Hydraulic diameter far from patch, $d_{h,Far}$
U	Velocity field name
phi	Flux field name
g <sup>¶</sup>	Gravitational acceleration
Tol	Tolerance for the Colebrook equation
Nitr	Max iterations for the Colebrook equation
fDiff	Max difference between <b>f</b> and <b>fInitial</b>



(A) Flow rate

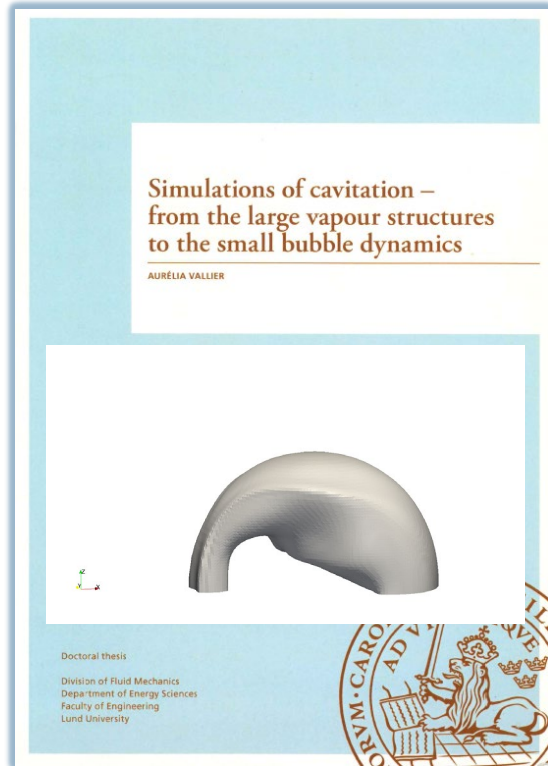


(B) Pressure probe

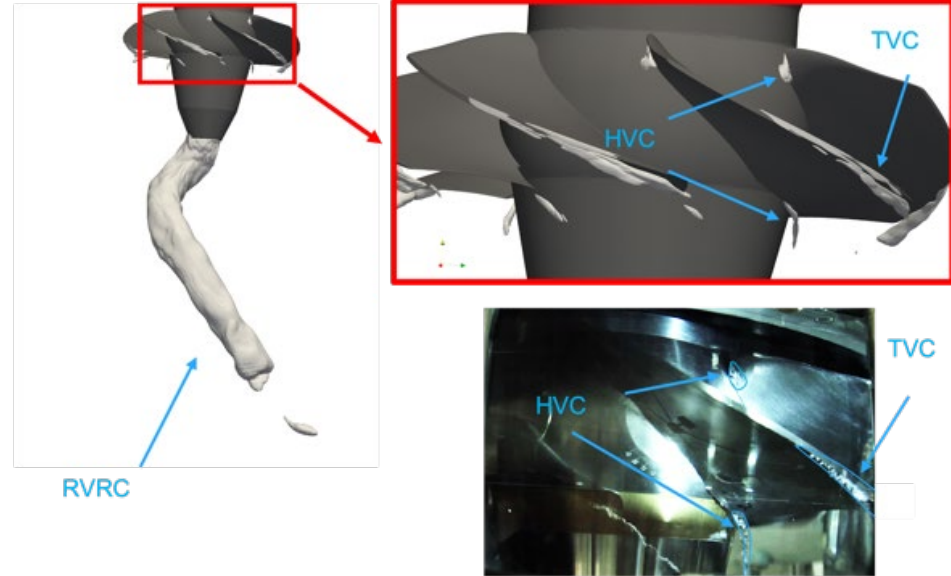
FIGURE 6. Flow rate and static pressure during the transient sequence. Wang et al. [7] is numerical results with MOC and Exp. is experimental results reported by Petit et al. [6].

# Studies of cavitation

## PhD thesis 2013 and post-doc 2020-2022



Post-doc Mohammad Hossein Arabnejad




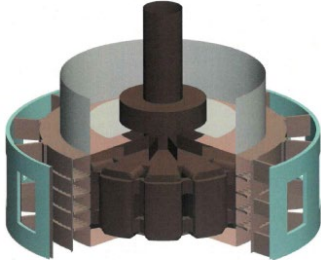
PL ( $\sigma = 0.31$ )

# Studies of cooling air flow in generators

## PhD theses, 2013, 2017 and 2018




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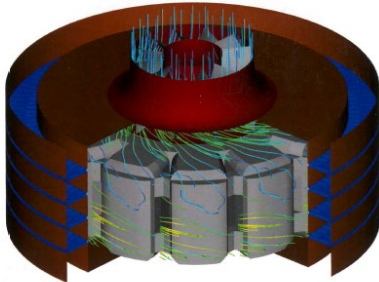


Prediction of Cooling Air Flow  
in Electric Generators

PIROOZ MORADNIA

*Department of Applied Mechanics*  
CHALMERS UNIVERSITY OF TECHNOLOGY  
Gothenburg, Sweden 2013


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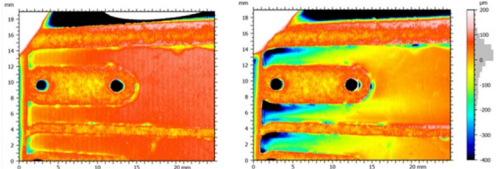
**Ventilation Flow Field  
Characteristics of a  
Hydro-Generator Model**  
An Experimental and Numerical Study

HAMED JAMSHIDI

*Department of Applied Mechanics*  
CHALMERS UNIVERSITY OF TECHNOLOGY  
Gothenburg, Sweden 2017

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PHD THESIS



**Flow over rough surfaces,  
and conjugate heat transfer,  
in engineering applications**

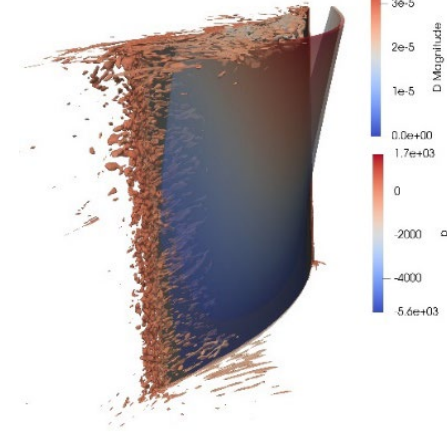
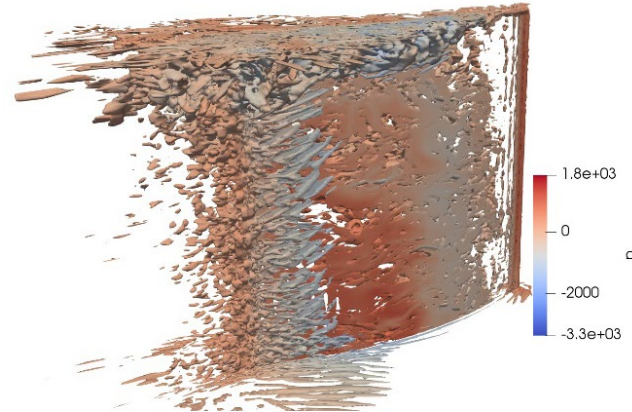
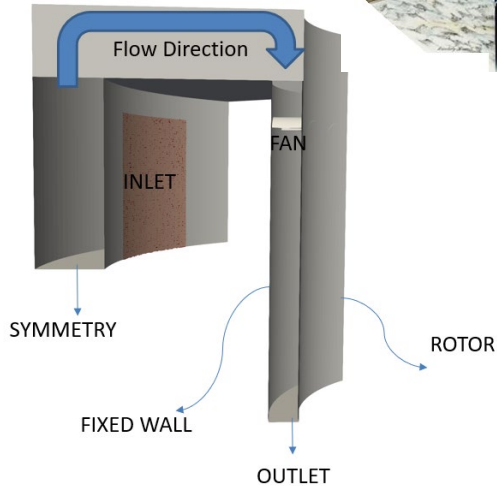
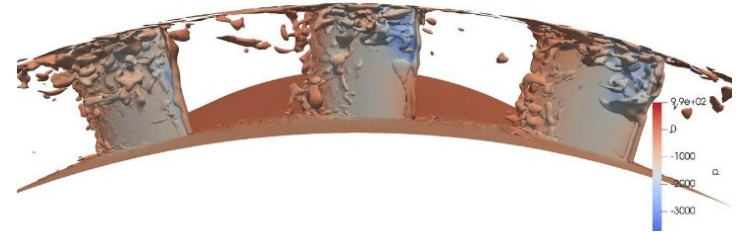
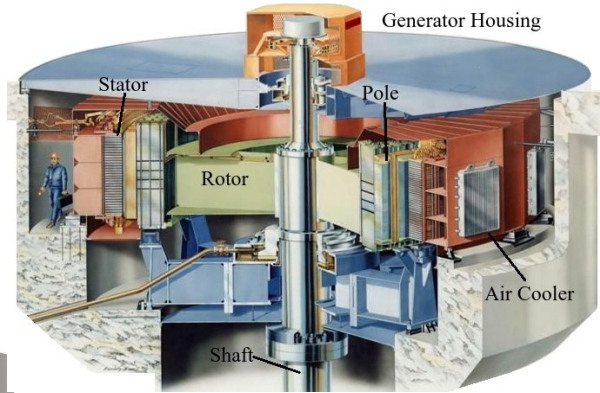
BERCELAY NIEBLES ATENCIO

DEPARTMENT OF MECHANICS AND MARITIME SCIENCES  
DIVISION OF FLUID DYNAMICS  
CHALMERS UNIVERSITY OF TECHNOLOGY  
Gothenburg, Sweden 2018  
www.chalmers.se



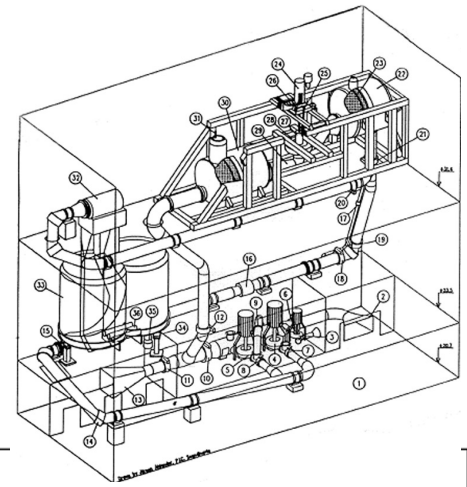
# Studies of cooling air flow in generators

Post-doc Saber Mohammadi, 2019-2021

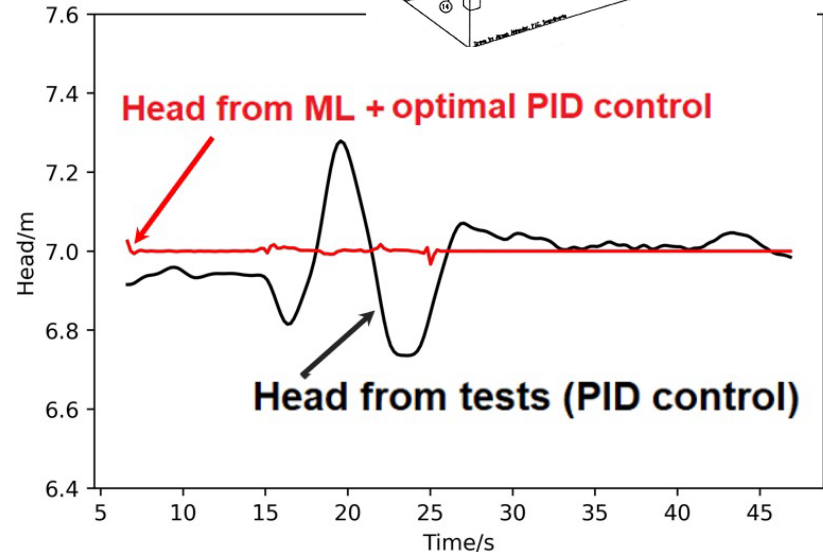
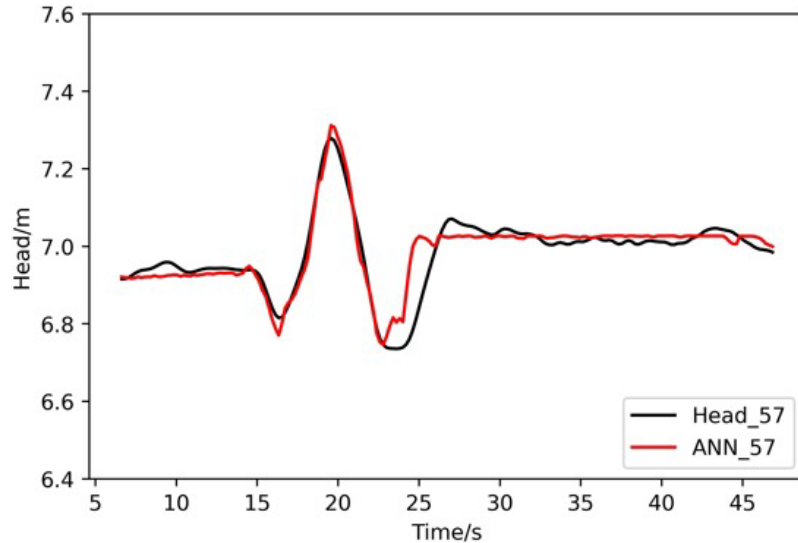


# Machine learning in hydropower

## Short PhD student pilot-project, Xiao Lang, 2022



Data\_57



# Present group, working in hydropower



Saeed Salehi



Martina Nobilo



Xiao Lang



Mohammad  
Sheikholeslami



Jonathan Fahlbeck



Håkan Nilsson

## Additional academic supervisors:

Wengang Mao<sup>1</sup>, Arash Eslamdoost<sup>1</sup>, Yujing Liu<sup>2</sup>, Rickard Bensow<sup>1</sup>

<sup>1</sup> Division of Marine Technology

<sup>2</sup> Department of Electrical Machines and Power Electronics

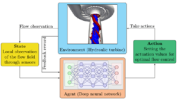
# Visit posters for SVC-financed projects!



## ARTIFICIAL INTELLIGENCE FOR ENHANCED HYDRAULIC TURBINE LIFETIME

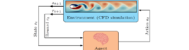
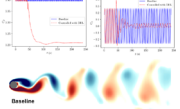
### Deep Reinforcement Learning for Active Flow Control

**BACKGROUND**  
In recent years, an extensive series of studies have been dedicated to understanding and describing the complex flow field and turbulence evolution during transient and start-of-operation of hydraulic turbines (see the below picture as an example). However, such investigations are restricted to one case at a time. Several deep learning (DL) and reinforcement learning (RL) approaches have been proposed to detect and mitigate the flow-induced instabilities in such conditions.



**VERIFICATION CASE STUDY**  
Vortex shedding behind a cylinder is investigated for verification. The actuator is a pair of perforated jets on top and bottom of the cylinder. The reward function is defined as the reduction of drag and the coefficient of lift. Through the RL, agent learns to minimize the drag and the coefficient by applying the optimum jet flow at each time step. The following picture illustrates a significant reduction of drag and lift forces as well as vortex shedding effects using DRL.

**AI IN FLUID MECHANICS**  
Recent artificial advancements in Artificial Intelligence (AI) have enabled tackling high-dimensional controlling and optimization problems. Deep Reinforcement Learning (DRL), as a combination of deep learning and reinforcement learning, has proven extremely successful control tasks at a sophisticated level, for instance, training an autonomous robot, learning the trajectory dynamics of multiple fish controlling a fluid-driven rigid body, and ship optimization.



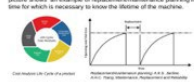
**DRL FOR HYDROPOWER**  
The most recent, a coupled DRL-CFD framework was developed within OpenFOAM, as depicted in the picture above. In this literature, in which the CFD solver was treated as a black box, how the DRL agent is implemented at a boundary condition, that is, how to sense the environment state, perform an action, and record the corresponding results. The picture below displays a simple framework of the developed DRL framework in which a deep neural network (DNN) is used as the decision maker (i.e., policy function).

**FUTURE PLANS**  
The next step is to apply the DRL-CFD algorithm to hydropower-related test cases, such as the literature in which the CFD solver was treated as a black box. How the DRL agent is implemented at a boundary condition, that is, how to sense the environment state, perform an action, and record the corresponding results. The picture below displays a simple framework of the developed DRL framework in which a deep neural network (DNN) is used as the decision maker (i.e., policy function).



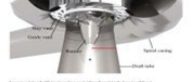
## CFD FOR HYDROPOWER LIFETIME ANALYSIS

**IMPORTANCE OF HYDROPOWER LIFETIME ANALYSIS**  
With more power from intermittent sources of energy entering the electric grid, hydropower is becoming increasingly important as necessary to safely operate the turbines during transient, planar maintenance, predict the lifetime of the hydropower plants, and estimate costs associated with new operating components. The left picture below shows a Life Cycle Cost Analysis that is based on the lifetime of the product (see picture). Low operating costs can lead to a higher profit. The right picture shows an example of replacement/maintenance planning in time for which it is necessary to know the lifetime of the machine.



**HOW CAN CFD BE INTEGRATED INTO THE LIFETIME ANALYSIS?**  
There has to be a need to predict the lifetime of a turbine. It is necessary to have a high-fidelity model of the full flow through the machine. Depending on the operating conditions, the different flow regimes can occur. The flow regimes are highly dependent on the turbine geometry. There is a significant impact on the forces acting on the parts of the turbine, such as the runner, blades, and other parts of the machine, such as the shaft, bearings and all other parts of the machine. The lifetime analysis, therefore, has to be able to handle the different flow regimes, and the different operating conditions. Computational Fluid Dynamics (CFD) results have been used to predict the required design data.

### CHOSEN TURBINE TYPE



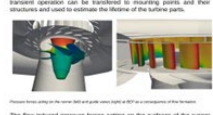
The flow-induced pressure fluctuations on the surfaces of the runner and guide vanes are shown in the picture above. The colors indicate the magnitude of the forces, with red showing the highest and blue the lowest magnitude. This is an example of data that can be transferred to a structural analysis software for assessment of fatigue and failure.

**Examples of CFD results**  
CFD is used to describe flow simulations, with which the mentioned flow features can be discovered and tracked during transient operation. For example, the formation of vortices in the draft tube during shut-down of a Kaplan turbine is visualized using the flow visualization in the picture below. The picture shows two different time instances during a shut-down operation. The left picture shows the flow at the best efficiency point (BEP), while the right picture shows the flow at partial condition.



It can be seen that the flow in the draft tube looks completely different depending on the current load of the turbine, which is here regulated by changing the opening of the governing valve. The different flow regimes are highly dependent on the turbine geometry. There is a significant impact on the forces acting on the parts of the turbine, such as the runner, blades, and other parts of the machine, such as the shaft, bearings and all other parts of the machine. The lifetime analysis, therefore, has to be able to handle the different flow regimes, and the different operating conditions. Computational Fluid Dynamics (CFD) results have been used to predict the required design data.

**Connecting CFD with structural analysis**  
The results obtained from CFD can be transferred to a software that performs structural analysis. In order to investigate the effect of the flow-induced forces on the structure, it is necessary to have a high-fidelity model of the full flow through the machine. Depending on the operating conditions, the different flow regimes can occur. The flow regimes are highly dependent on the turbine geometry. There is a significant impact on the forces acting on the parts of the turbine, such as the runner, blades, and other parts of the machine, such as the shaft, bearings and all other parts of the machine. The lifetime analysis, therefore, has to be able to handle the different flow regimes, and the different operating conditions. Computational Fluid Dynamics (CFD) results have been used to predict the required design data.



The flow-induced pressure fluctuations on the surfaces of the runner and guide vanes are shown in the picture above. The colors indicate the magnitude of the forces, with red showing the highest and blue the lowest magnitude. This is an example of data that can be transferred to a structural analysis software for assessment of fatigue and failure.



## MACHINE LEARNING IN A RENEWABLE ELECTRIC ENERGY SYSTEM

### – for hydraulic-mechanical-electrical coupling mechanisms and optimal hydropower plant operations.

**BACKGROUND**  
Balancing electricity consumption and production is crucial for stable electrical grid operation. With the rise of renewable energy sources, such as wind and solar power, there is an increasing need for power grid balancing. Hydropower plants (HPPs) have become an important asset for grid balancing and support, and need to continuously adjust their operational parameters to balance power production and demand.

**AIMS AND METHODOLOGY**  
Data collection/utilization framework/regulation for the Swedish hydropower industry and data identification.



**IMPROVE: Great Frequency Stability  
HPPs, Increase Performance/Quality  
REDUCE: Hydrop Turbine Wear/Tear**

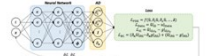
**POTENTIAL OUTCOMES**  
• A framework for collecting/utilizing big data in the Swedish hydropower industry for optimal HPPs-operation.  
• An optimal maintenance plan for HPPs to maximize their efficiency and lifespan.

**CONTRIBUTION**  
This project will contribute to the UN sustainable goals 7, Affordability and clean energy to reduce poverty and improve lives, and 13, Climate action to combat climate change and its impacts. The project will contribute to the UN sustainable goals 7, Affordability and clean energy to reduce poverty and improve lives, and 13, Climate action to combat climate change and its impacts. The project will contribute to the UN sustainable goals 7, Affordability and clean energy to reduce poverty and improve lives, and 13, Climate action to combat climate change and its impacts.



## MULTI-FIDELITY PHYSICS-INFORMED NEURAL NETWORK TO SOLVE PARTIAL DIFFERENTIAL EQUATIONS, an innovative approach to model fluid dynamics in hydropower

**Artificial neural networks for hydropower**  
Since the advent of the 19<sup>th</sup> century, artificial neural networks have included great capability in different fields, including engineering, medicine, finance, and many different types of neural networks. Deep neural networks have shown a much better performance as shown in Fig. 1.



**Example of one-dimensional convection-diffusion of fluid flow**  
is shown in Fig. 2 that a PINN can solve 1D convection-diffusion of fluid flow with good accuracy by only having the governing equations of the system and data at the initial time. In this case, no data was available in the internal field and boundaries, and the flow behavior was fitted through inclusion of the governing equations in the loss function (Eq. 2).

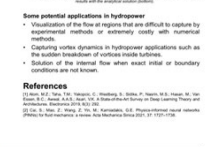


**However, the problem with using deep neural networks for hydropower applications can be summarized in two points:**

1. Deep neural networks are data-hungry (Fig. 1) and providing a high amount of data in hydropower applications can be prohibitively expensive.
2. Deep neural networks for these technologies are gathered from different sensors and cameras and are not all at the same quality of fidelity.

**Multi-Fidelity Physics-Informed Neural Networks for Hydropower**  
Following with the points mentioned above, a prior understanding of the physics of the problem like the governing equations of the system can come to the rescue. Here is where Physics-Informed Neural Networks (PINNs) come to play. PINNs can solve flow physics problems by governing equations and they can also take advantage of available data, even with different levels of fidelity. Two main features of PINNs are as follows:

1. Taking governing equations, boundary conditions, and/or initial conditions of the partial differential equations as input.
2. Using data with different levels of fidelity to overcome the local condition of the system or compensate for unknowns in governing equations.



# Some notes on the ALPHAEUS EU project...



# Low head pumped hydro storage

- ALPHEUS – EU H2020
  - Heads from **2 – 20 m**
  - Power of **10 MW** / unit
  - Round-trip efficiency of **70 – 80%**
  - Asses **environmental** and **ecological effects**
- Allow energy storage in flat regions
  - E.g. south of Sweden, Denmark, Netherlands, etc.
  - Energy islands with the sea as one *reservoir*
- At Chalmers we evaluate contra-rotating pump-turbines
  - Stationary operations
  - Transient procedures to limit detrimental loads

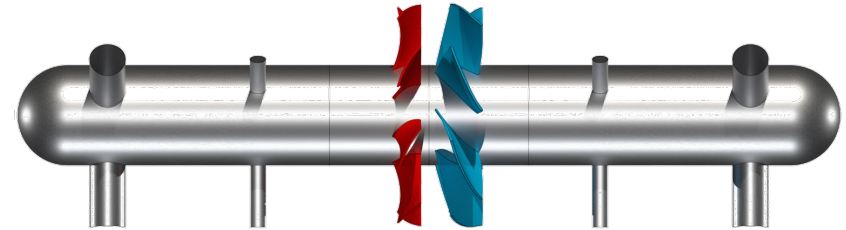


Figure: Shaft driven contra-rotating pump-turbine in model scale

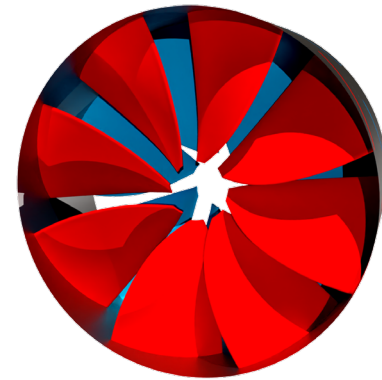
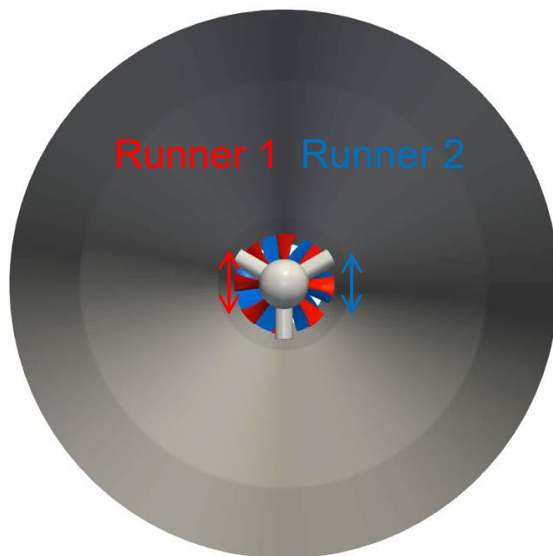
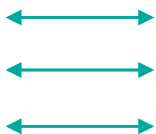


Figure: Rim driven contra-rotating pump-turbine

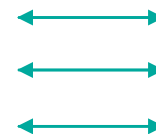
# Shaft driven contra-rotating pump-turbine

Model scale

## Pump Mode



## Turbine Mode



### Operating conditions

Power	49 kW
Flow rate	420 l/s
Net head	10 m
Hydraulic efficiency	87 %

### Operating conditions

Power	17 kW
Flow rate	290 l/s
Net head	7 m
Hydraulic efficiency	89 %

# Thank you for your attention!



## Acknowledgements:

- SVC
- The ALPHEUS project
  - EU Horizon 2020, No 883553.
  - Website: <https://alpheus-h2020.eu/>
- NAISS
  - Grant agreement No. 2022-06725
- OpenFOAM developers and community



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