Machine learning-assisted fan design: trends, challenges and applications

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Prompt to ChatGPT4.0: Estimate the dimensions, power absorption and rpm of an axial fan that operates in an air-cooled condenser with 333 m^3/s of volumetric flow rate and 115 Pa of static pressure rise.

Power input to the air (air power):

$$P_{\text{air}} = Q \times \Delta P = 333\,\text{m}^3/\text{s} \times 115\,\text{Pa} = 38,295\ \text{W} \approx 38.3\,\text{kW}$$

Assuming **fan total efficiency** (including motor & drive losses) ≈ 70%:

$$P_{\text{shaft}} = \frac{P_{\text{air}}}{\eta} = \frac{38.3}{0.70} \approx 54.7\,\text{kW}$$

Use the **specific speed** (dimensionless) and **fan laws** to estimate diam

Let's assume a **moderate-speed axial fan** operating at ~400 RPM.

From fan similarity laws:

$$Q \propto D^3 \cdot N \Rightarrow D \propto \left(\frac{Q}{N}\right)^{1/3}$$

$$D \approx \left(\frac{333}{400}\right)^{1/3} \approx 1.88\,\text{m}$$

👉 A fan diameter of **~1.8–2.2 meters** is a reasonable starting point.

4. Tip Speed Consideration:

Keep **tip speed below 120 m/s** to limit noise and avoid efficiency loss.

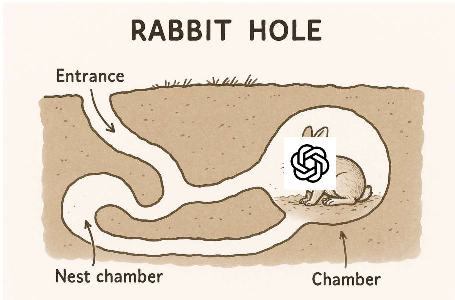
$$U_{\text{tip}} = \pi \cdot D \cdot N/60$$

Using D = 2.0 m, solve for max RPM:

$$N = \frac{60 \cdot U_{\text{tip}}}{\pi \cdot D} = \frac{60 \cdot 120}{\pi \cdot 2} \approx 1,146\,\text{RPM}$$

So, a speed of **<1000 RPM is safe**, and 400–800 RPM is typical for large axial fans.

And down the rabbit hole, with «stage» design, velocity triangles and on…

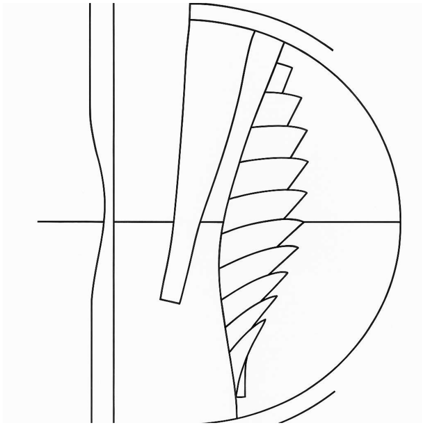


Prompt to ChatGPT4.0: Estimate the dimensions, power absorption and rpm of an axial fan that operates in an air-cooled condenser with 333 m^3/s of volumetric flow rate and 115 Pa of static pressure rise.

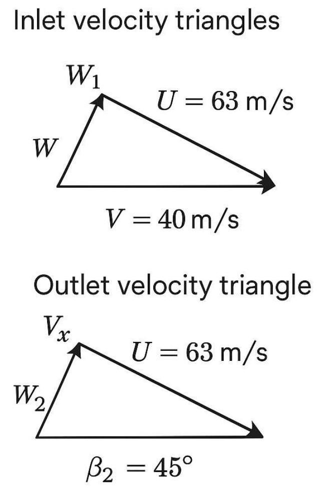
Summary of Key Parameters:

Parameter	Value
Airflow Rate (Q)	333 m^3/s
Static Pressure Rise	115 Pa
Power (input to air)	~38.3 kW
Shaft Power Required	~54.7 kW (at 70% eff.)
Fan Diameter Estimate	1.8 – 2.2 m
RPM Range	400 – 800 RPM
Blade Type	Aerofoil, adjustable pitch
Hub-to-Tip Ratio	0.3 – 0.5

Blade layout (??)



Velocity triangle (?)



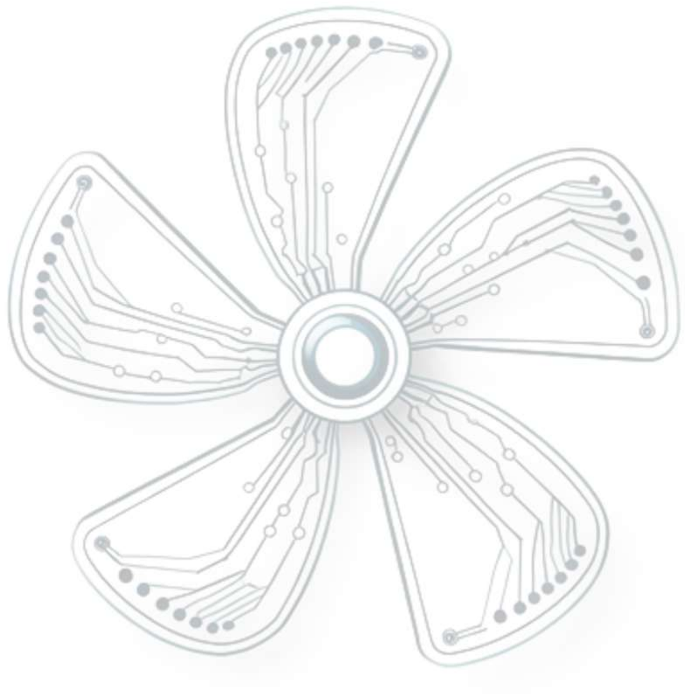
AI	TM experts
400-800 rpm	151 rpm
$\psi = 0.0486$	$\psi = 0.093$

A WELL-FOUNDED CONCERN

Is AI the future of turbomachinery and fans?

OUTLINE

- Part 1: Introduction to Machine Learning and Its Role in Fan Research (15 min)
- Part 2: Case Studies and Lesson Learnt on ML and Fans (30 min)
- Part 3: Conclusion & Q&A (10 min)



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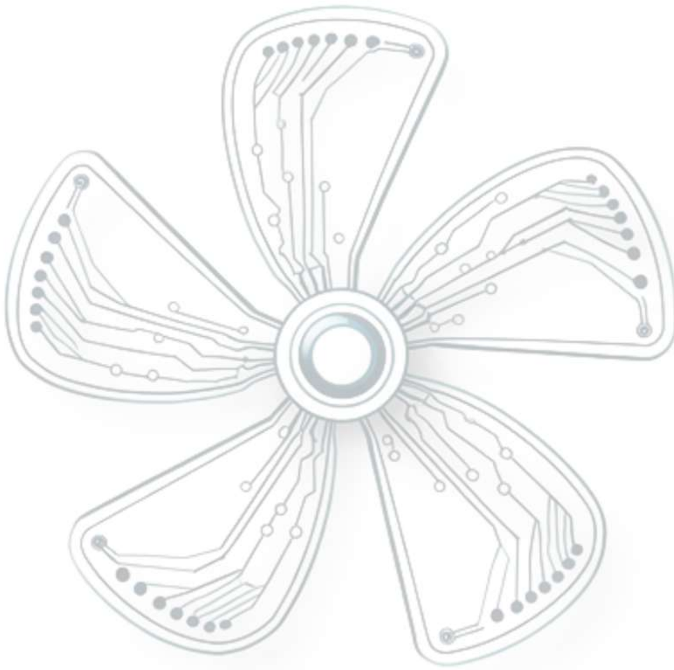


Part 1: Introduction to Machine Learning and Its Role in Fan Research

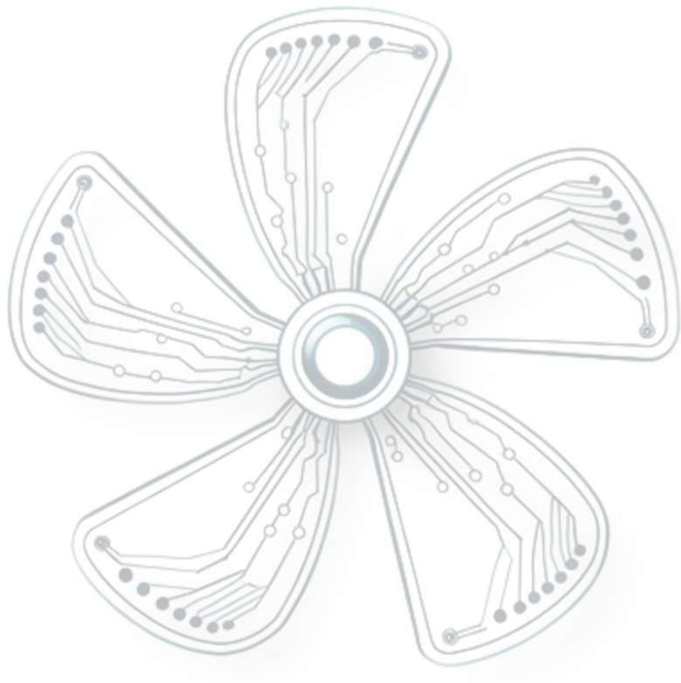
Basics of Machine Learning

- Supervised, Unsupervised, and Reinforcement Learning
- Data sources: IoT sensors, performance testing, simulations

Context

- The growing role of AI/ML in engineering, manufacturing, and aerodynamics

ML Applications in Fan Technology



General Definition - Arthur Samuel's Definition (1959):
"Machine learning is the field of study that gives computers the ability to learn without being explicitly programmed."

Technical Definition:
Machine learning is the study of algorithms that improve automatically through experience and data, often using statistical and probabilistic methods to identify patterns and make informed decisions.

Tom Mitchell's Definition (1997):
"A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E".

Practical Definition (Industry-focused):
Machine learning is the process of training computers to recognize patterns and make decisions based on data, used in a wide range of applications.

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Practical Definition (Engineering-focused)
A complex way to derive very complex and powerful models.

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—Tom Mitchell, 1997

Artificial Intelligence

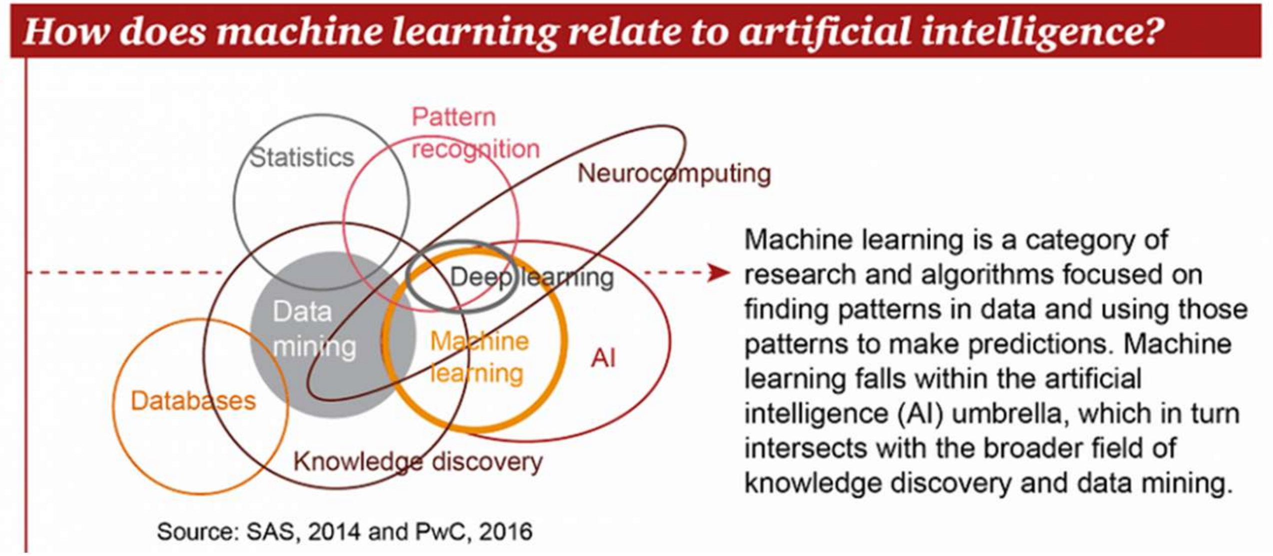
Involves all those operations characteristic of human intellect and performed by computers. These include planning, language comprehension, object and sound recognition, learning and problem solving. Not all AI are based on statistical learning as they can be condition-based programs (e.g. Chatbot)

Machine Learning

Represents a way to "automate" the construction of an analytical model to give computer systems the ability to "learn" from data, without being explicitly programmed. Training phase involves the use of large amounts of data and an efficient algorithm in order to adapt (and improve) according to the situations that occur.

Deep Learning

Uses huge models of neural networks with various processing units; exploits computational advances and training techniques to learn complex models through an enormous amount of data. Common applications include image and speech recognition.



ML MODEL

Data collection → Model building → Learning → Training → Evaluation

Level of development in TM

Established
- Open Research Data – papers
- Private Data – company and sensitive data
- Sensor Data, Logs & Events
- Data from manufacturers

Embrional
- Open Source Datasets
- Surveys & Feedback
- Web Scraping & APIs
- Crowdsourced Data

Sources of data for ML applications can be diverse.

Common examples include experimental data, numerical simulations, IoT, sensor networks, and more.

Although the ML and TM communities are growing, significant efforts must still be made to create **open datasets** and **share** both data and knowledge.

The **confidentiality** of data may, however, partially hinder its development.

BUILDING A MODEL

Data collection → Model building → **Learning** → Training → Evaluation

Level of development in TM		
Established	Supervised Learning	
Growing	Unsupervised Learning	
Embrional	Reinforcement Learning (RL)	

Supervised Learning

- Learns from **labeled data** (input-output pairs).
- Used for **classification** (e.g., fault diagnosis) & **regression** (e.g., performance prediction)

Unsupervised Learning

- Learns from **unlabeled data,** discovering hidden patterns.
- Used for **clustering** (e.g., pattern recognition) & **dimensionality reduction** (e.g., PCA).

Reinforcement Learning (RL)

- Learns by **interacting** with an environment and receiving **rewards/penalties.**
- Used where **self-learning** is needed (e.g. controllers).

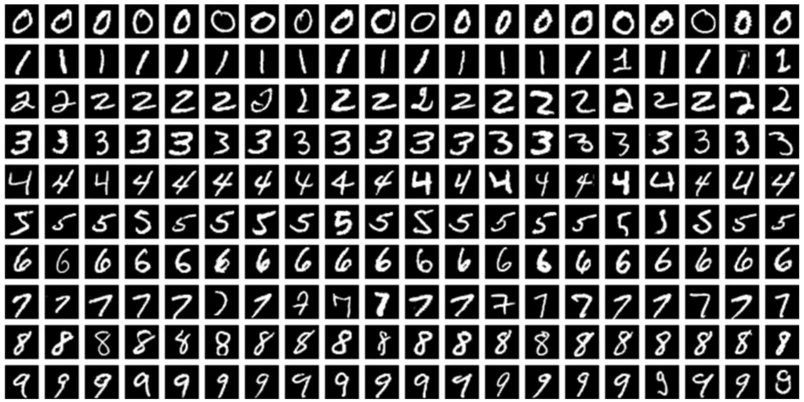
Practical Definition (Engineering-focused)

A complex way to derive very complex and powerful models.

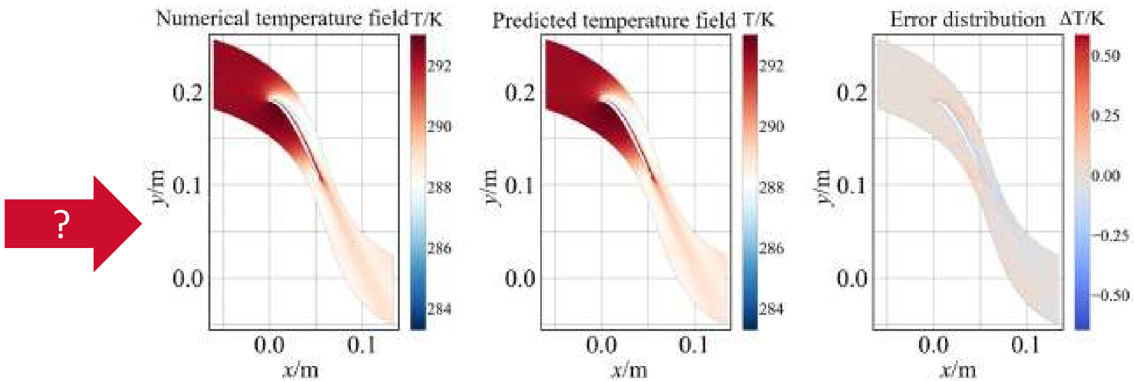
In engineering applications, ML can be used to solve a **wide range of tasks**, from computer vision to anomaly detection.

Similarly, ML models can be used in turbomachinery applications as a **more powerful alternative** to statistical/traditional methods.

However, transferring the already established knowledge of ML to turbomachinery (and fans) is still an open debate.



"The MNIST Database of handwritten digits", LeCun et al.



"A fast prediction model of blade flutter in turbomachinery based on graph convolutional neural network", Liu et. Al - adapted

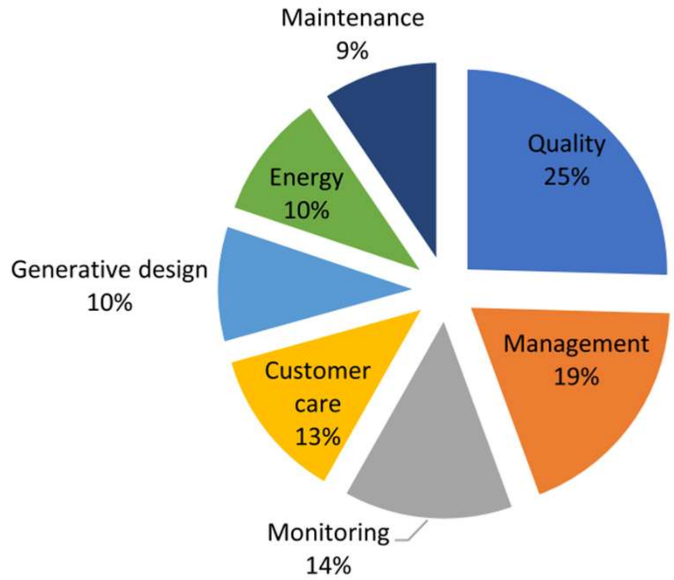
Machine Learning (ML) and Artificial Intelligence (AI) are widely used across various industrial applications, from design to customer care.

However, rather than viewing AI/ML as a highly adaptable and intelligent system, it is more accurate to see it as a collection of specialized models, each excelling at a specific task.

These models have limited ability to extrapolate or generalize and, in most cases, cannot learn from new experiences unless explicitly programmed to do so.

This approach is known as **Narrow AI**, emphasizing its restricted scope of operation.

Narrow AI can be considered the current level of technological development in turbomachinery



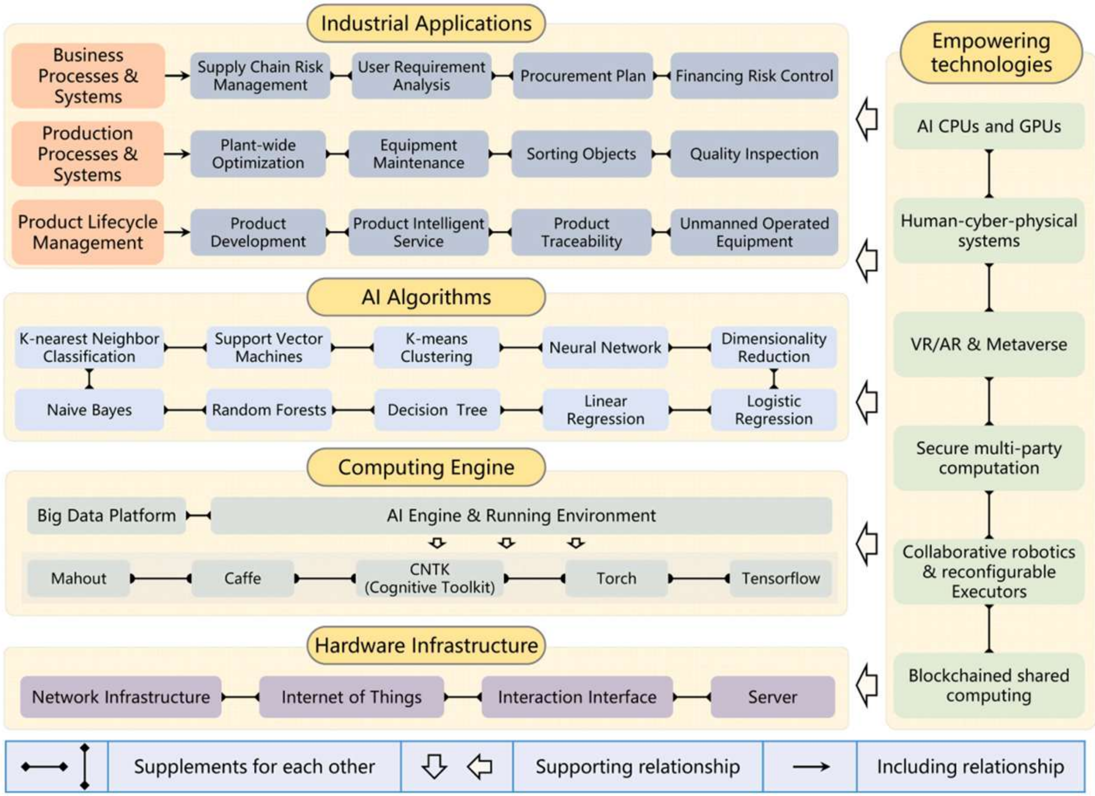
"Integrating artificial intelligence in industry 4.0: insights, challenges, and future prospects–a literature review", Gabsi A.

In industry 5.0 a shift from Narrow AIto a General AI or Industrial AI must occur.

This is a long process, as it would require to shift the paradigm of current models from basic learners to advanced (and expensive) smart systems.

This novel and complex digital system will be founded on three pillars:

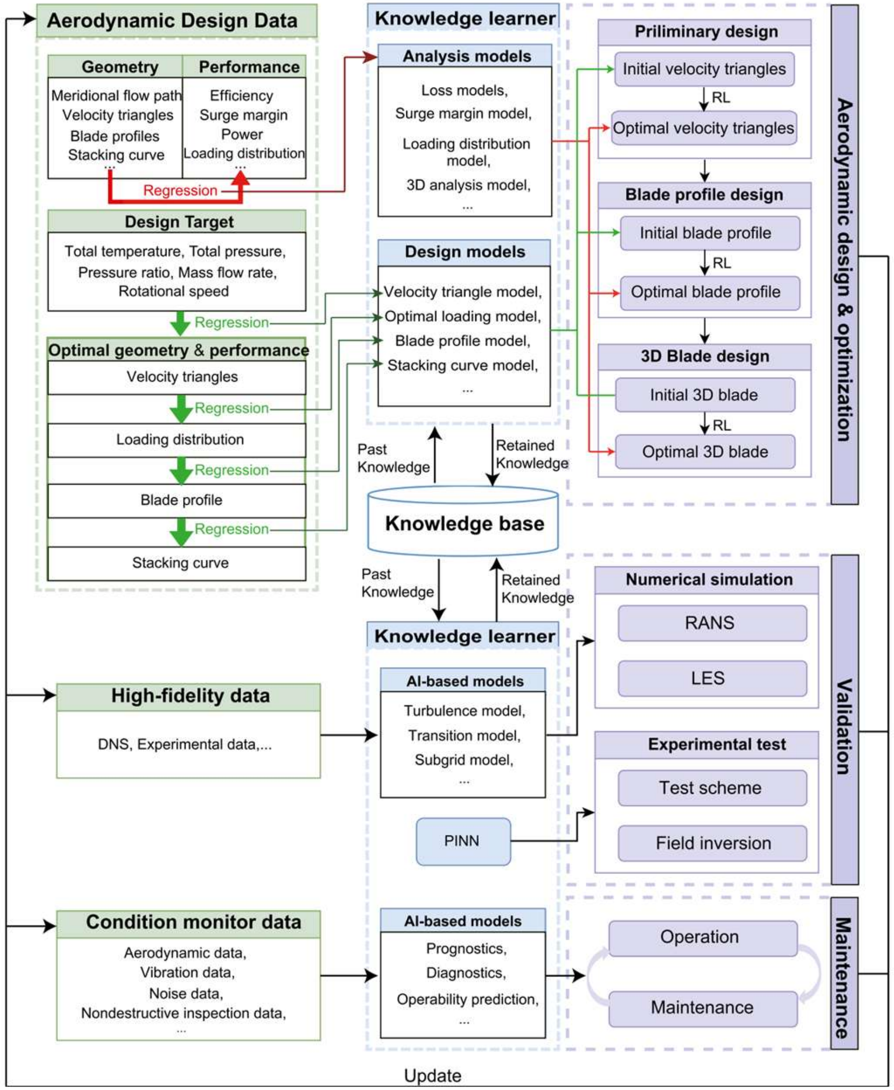
1. Collaborative intelligence
2. Self-learning intelligence
3. Crowd intelligence



Reference frame of IndAI applications – Leng et al.

Narrow AI can be considered the current level of technological development in turbomachinery

- During the turbomachinery **design** phase, ML can assist, enhance, or even fully replace existing models. ML can optimize blade shape or predict TM performance using a computation-free approach (as shown later).
- In the **validation** stage, ML can be applied to advanced turbulence modeling, surrogate modeling, or flow field analysis and investigation using experimental data.
- ML can also be utilized for operations and maintenance (**O&M**) monitoring and decision-making.
- Each of these tasks requires different methods, and within this framework, they are largely independent of one another.



The role of ML within TM applications – Zou et al.

The great increase of data-driven methods applied in turbomachinery especially for aerospace applications, is gradually leading to novel developments also for industrial fans.

Notable applications:

- Exploration of performance charts: unsupervised methods and dimensionality reduction
- Design and optimization: supervised methods for blade shape and geometrical parameter optimization (e.g. volute shape)
- Prognosis & fault diagnostic: : supervised methods to assess reliability, damage and RULE of fans
- Control and efficiency improvement: supervised and reinforced learning for energy consumption reduction, on large systems

Overview of The Best 2020 AxialFlow Fan Data and Inclusion in Similarity Charts for the Search of the Best Design

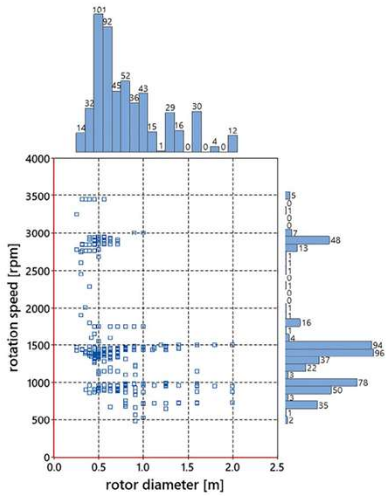
Masi M., et al. *Journal of Turbomachinery 144.9 (2022): 091012.*

Scopes: Exploration of catalogue data

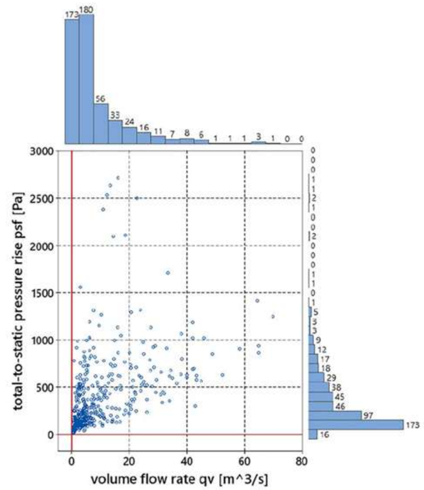
Methodology: a statistical survey of 500 axial-flow fan performance based on data from catalogues of major manufacturers and compares the resulting Cordier lines with optimum fan designs from empirical or computational fluid-dynamics (CFD)-based models available in the literature

Model: statistical survey

Result: determination of the optimal characteristics of the fan designs, as well as novel and old trends



Marginal plot of the rotation speed against fan diameter



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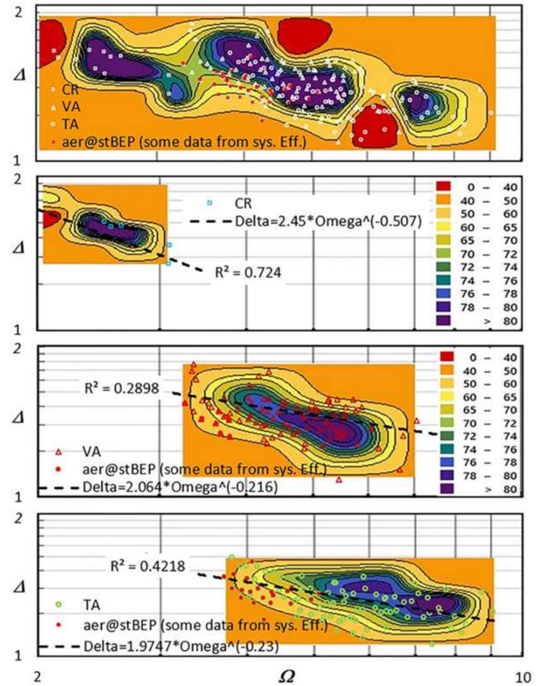


Aeraulic efficiency Balje charts of year 20 ducted fan types (top), CR fans (top-middle), VA fans (middle-bottom), and TA fans (bottom)

Machine-learning and CFD based optimization and comprehensive experimental study on diagonal flow fan for energy conservation and efficiency enhancement

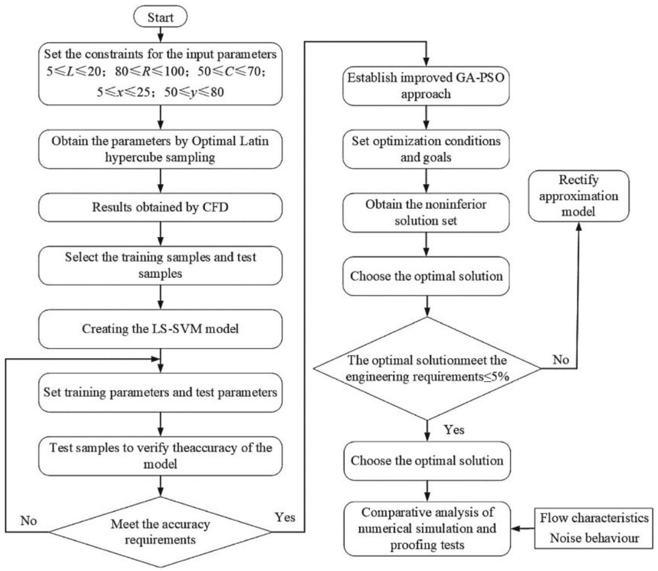
Zhou, Shuiqing, et al., Engineering Applications of Computational Fluid Mechanics 18.1 (2024): 2310608, 2024.

Scopes: Multi-objective optimization (pressure, sound emissions and efficiency) of the outlet guide vane of a mixed flow fan

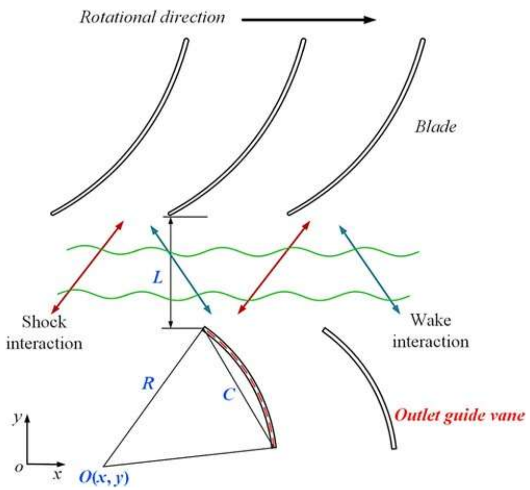
Methodology: rotor-stator axial spacing, OGV camber line radius, length and location are varied and simulated through CFD. LS-SVM is trained and used as evaluation function in GA-PSO coupling.

Model: Least Squares – Support Vector Machine + Genetic Algorithms with Particle Swarm Optimization

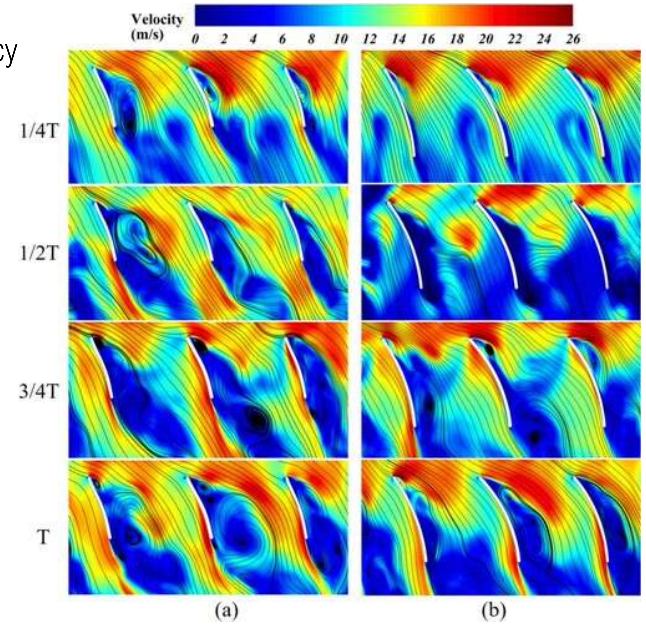
Result: 106 Pa increase in total pressure, a 3.6 dB reduction in noise levels, and 16.3% enhancement in total pressure efficiency



Framework



Optimization parameters



Comparison between baseline and optimized geometries

Off-design performance analysis of a radial fan using experimental, computational, and artificial intelligence approaches

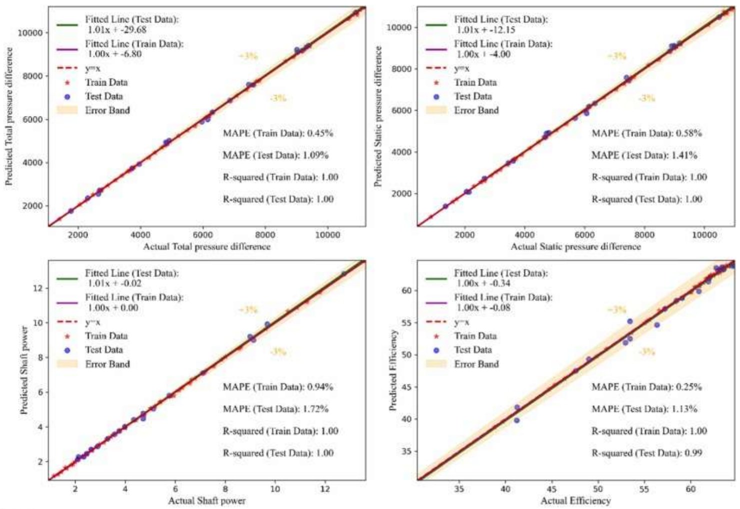
Moradihaji et al., European Journal of Mechanics-B/Fluids 104 (2024): 150-172.

Scopes: Predict the off-design performance of a radial fan using machine learning

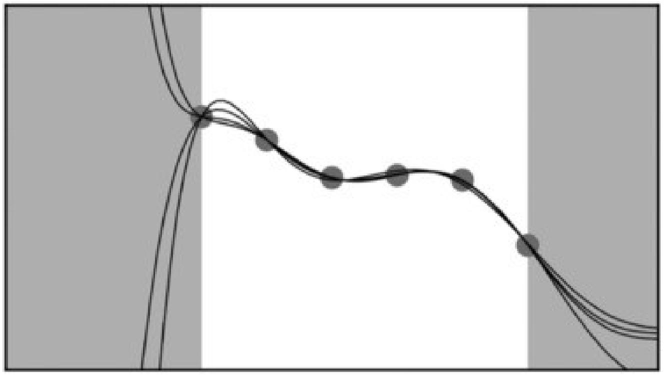
Methodology: 70 numerical simulations of off-design operations, the artificial neural network is used as a surrogate performance map of the fan

Model: Deep Artificial Neural Networks, Support Vector Machine, Random Forest

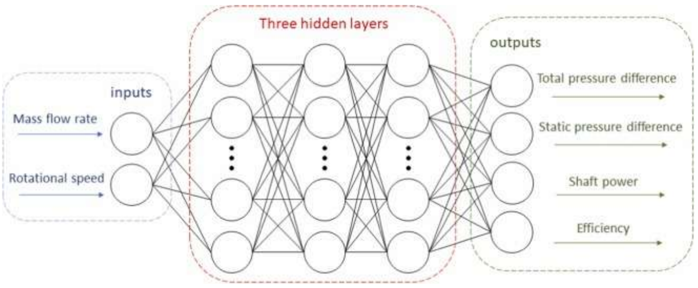
Result: results are comparable to CFD simulations, however the model shows limited extrapolation capability



Model performance



Model extrapolation



Surrogate mdoelling of map performance

Predicting the Operability of Damaged Compressors Using Machine Learning

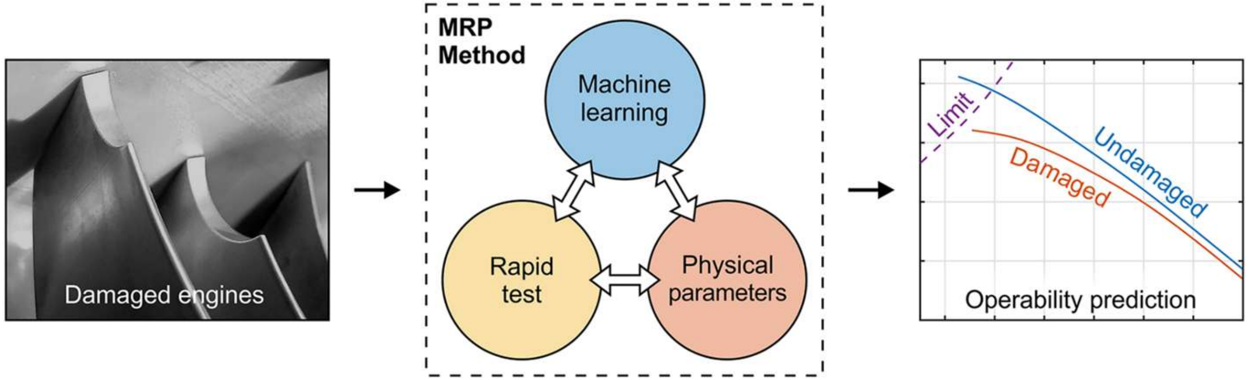
Taylor J. V., European Journal of Mechanics-B/Fluids 104 (2024): 150-172.

Scopes: Predict the off-design performance of a radial fan using machine learning

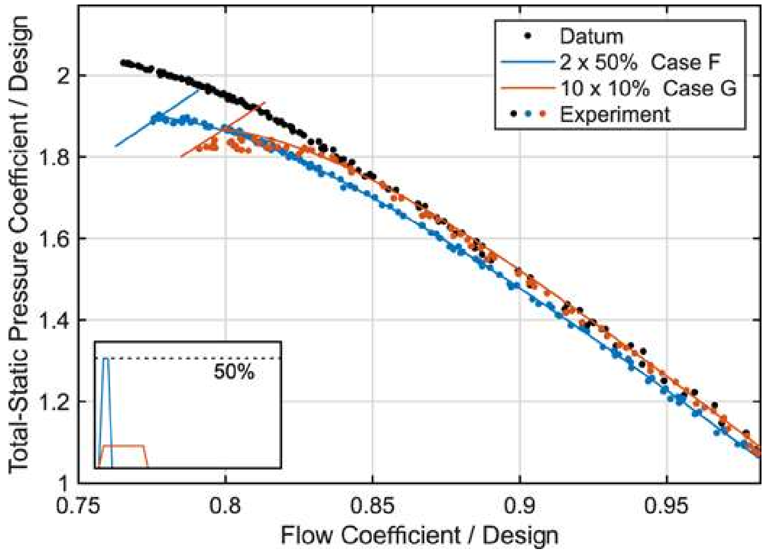
Methodology: novel MRP method, composed by machine learning, rapid test to provide the training experimental data, and physical parameters drawn from engineering

Model: Neural networks

Result: the method can predict the operability with an accuracy of 2% in a 95% confidence interval



Prediction of the blade damage through MRP method



Model performance with different levels of damage

Fan Fault Diagnosis Using Acoustic Emission and Deep Learning Methods

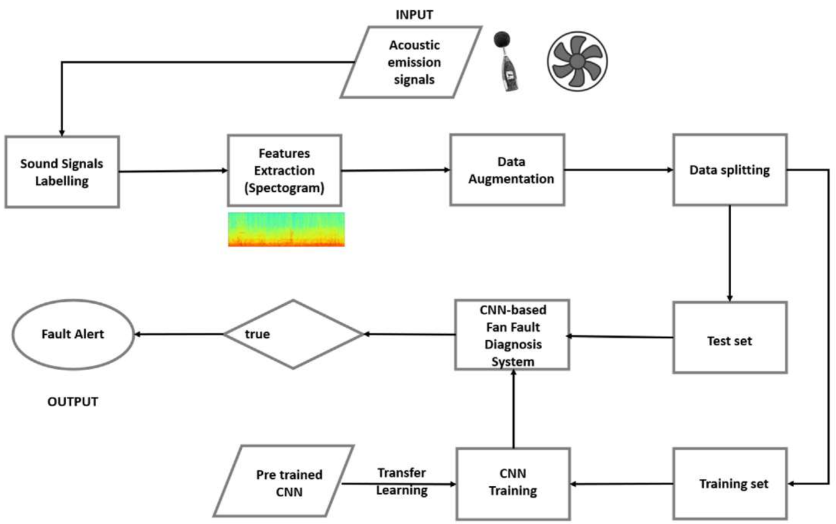
Ciaburro, Giuseppe, et al. *Informatics*. Vol. 10. No. 1. MDPI, 2023.

Scopes: Detection of possible failure condition of an axial fan

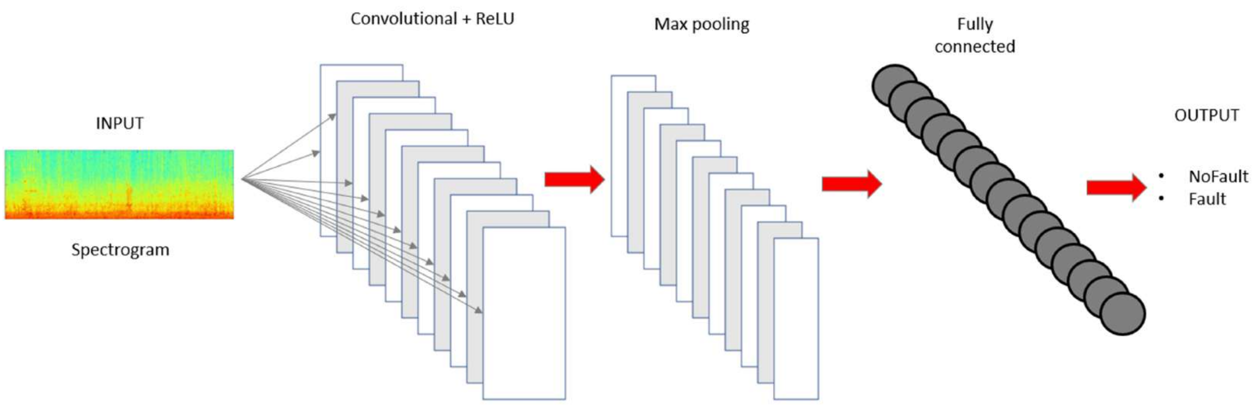
Methodology: the recording of the acoustic emission and the failure diagnosis using deep learning was evaluated for the detection of dust deposits on the blades of an axial fan

Model: Convolutional Neural Network for a binary classification problem

Result: 95 % of accuracy in detecting blade fouling



Fault diagnosis CNN-based framework



From spectrogram to blade state prediction

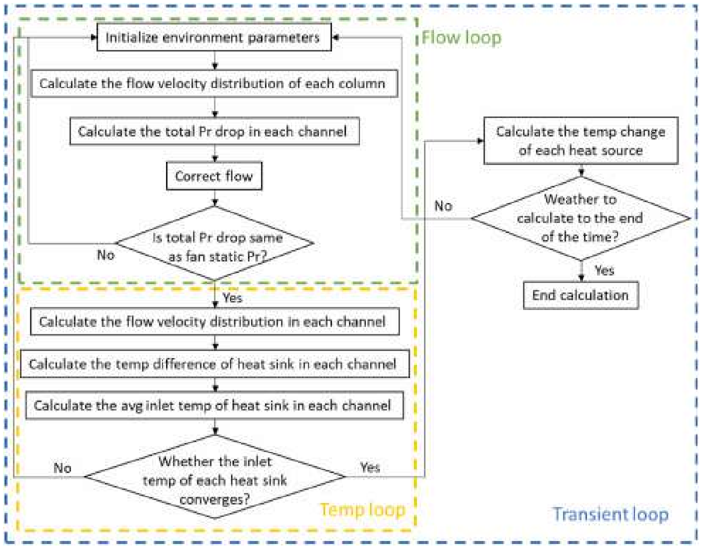
Optimized and Energy Efficient Server Fan Control Using Deep Reinforcement Learning Method.
Fulpagare, Yogesh, et al., Journal of Building Engineering (2025): 112306.

Scopes: Development of a controller to achieve energy consumption of server fans

Methodology: controllers are implemented in an experimental apparatus, the controller takes decisions in real-time and is optimized during the tests.

Model: Deep Deterministic Policy Gradient algorithm (DDPG)

Result: the fan power consumption and overheating are reduced to 53 % and 9 %, respectively



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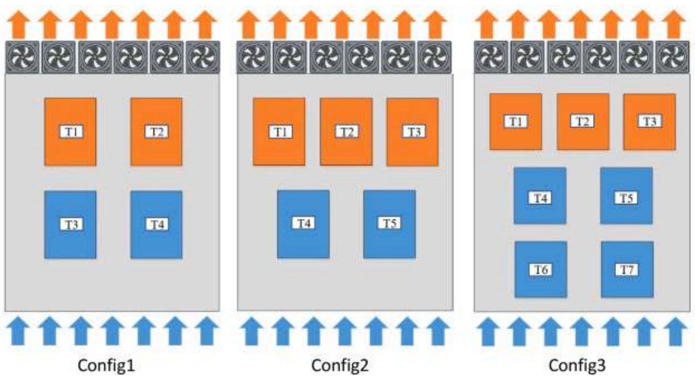
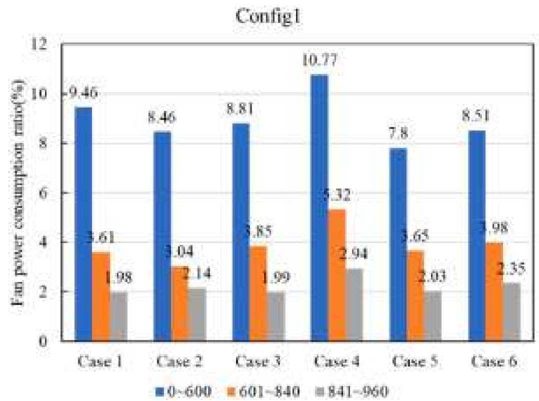


Fans and system configurations



Fan power for different scenarios - adapted

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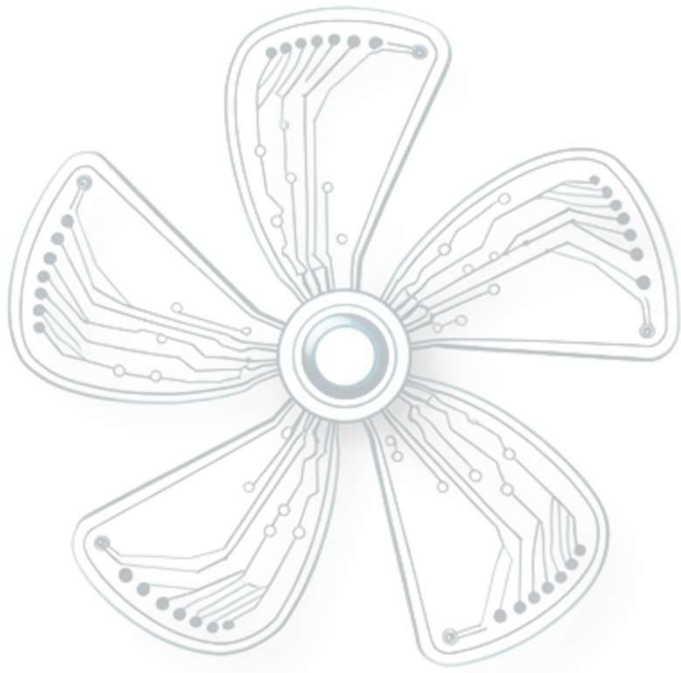

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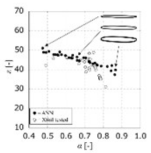
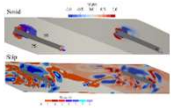
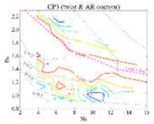


Surrogate-based optimization of truly reversible blade profiles for axial fans

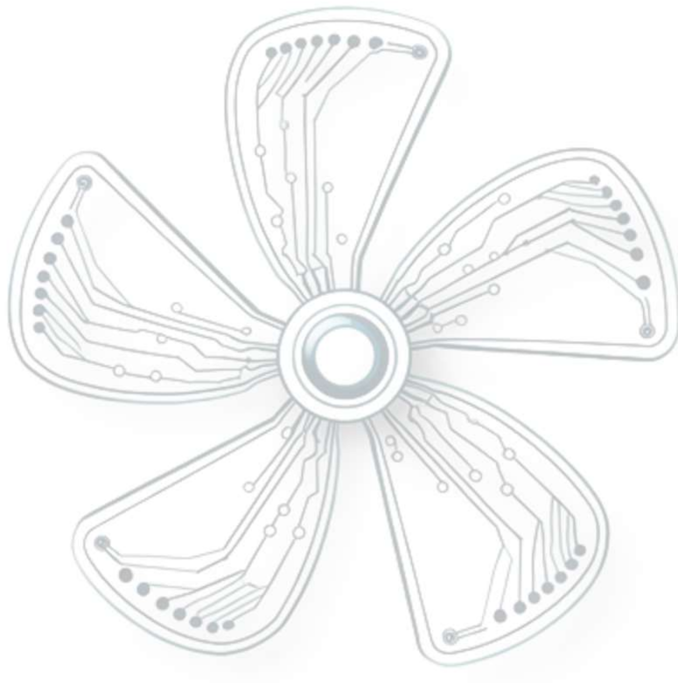


Machine-learning clustering methods applied to detection of noise sources in low-speed axial fan

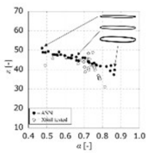


A multidimensional extension of Balje chart for axial flow turbomachinery using artificial intelligence-based meta-models

Lesson learnt & practical tips



Part 2: Case Studies and Lesson Learnt on ML and Fans



Surrogate-based optimization of truly reversible blade profiles for axial fans

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Lesson learnt & practical tips

This work presents a study on the SM based methodology to obtain a set of optimized aerofoils shapes for the use in reversible fan blading. It addresses the following question: how meta-model techniques affect results of multi objectives optimization and how these meta-models should be exploited in an optimization test-bed.

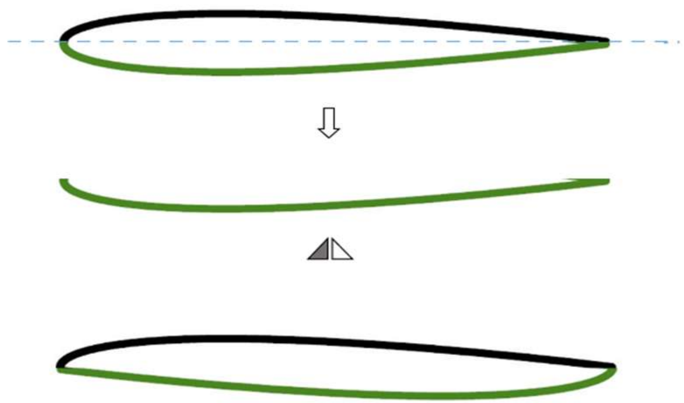
Objective functions

1) Aerodynamic efficiency

$$\varepsilon = \frac{C_{LS}}{C_D}$$

2) Stall margin

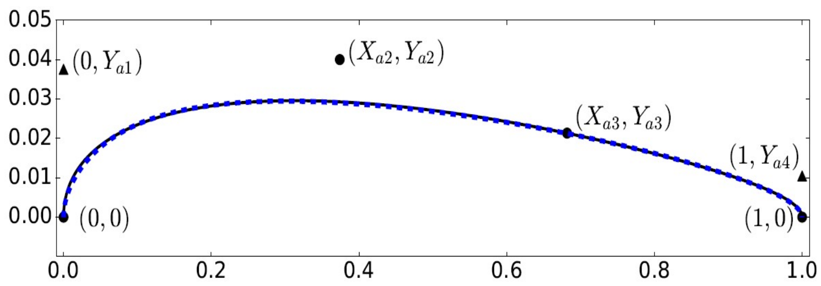
$$\alpha = \frac{AoA\left(\max(C_L)\right) - AoA(C_{LS})}{AoA\left(\max(C_L)\right)}$$



Truly reversible airfoil

Geometry parameterization

The selected scheme is a 6th degree **B-spline** parameterization



Angelini, G., Bonanni, T., Corsini, A., Delibra, G., Tieghi, L., & Volponi, D. (2018). On surrogate-based optimization of truly reversible blade profiles for axial fans. *Designs*, *2*(2), 19.

Optimization algorithm

Non-dominated sorting genetic algorithm (**NSGA-II**), Deb 2012. NSGA-II combines **non-dominated sorting** with a diversity-preserving mechanism based on **crowding distance**

Test matrix

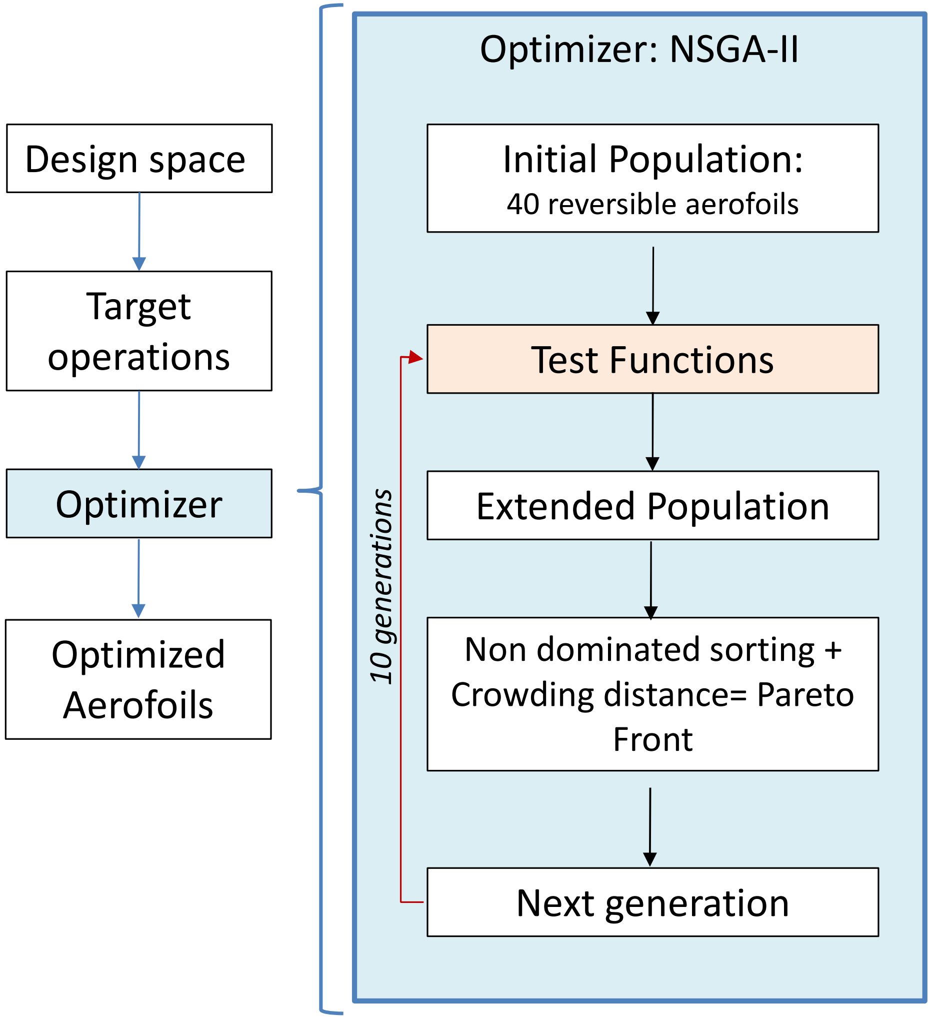
A matrix of **25 optimization cases** representing common operations for tunnel and metro fans was defined by means combinations of 5 values *Re* and 5 values C_{LS}

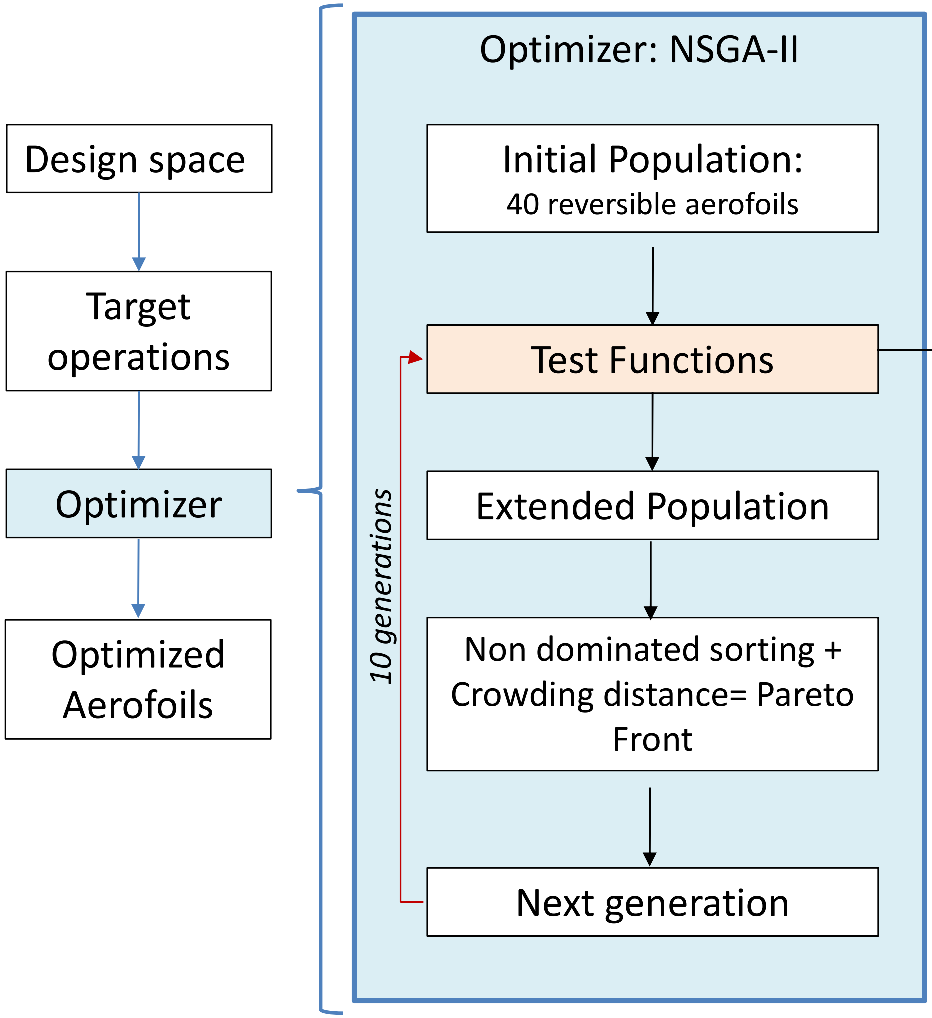
Re	300000	675000	1050000	1425000	1800000
C_{LS}	0.1	0.3	0.5	0.7	0.9

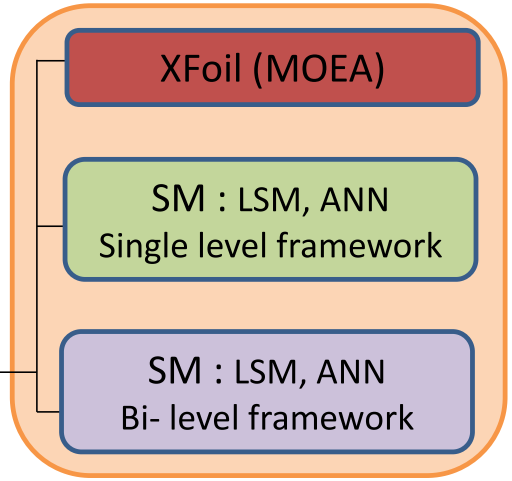
Data Sampling

The **design space** includes 8 parameters

$$F = (X_{a2}, Y_{a2}, Y_{a1}, X_{a3}, Y_{a3}, Y_{a4}, Re, C_{LS})$$


Design space
Target operations
Optimizer
Optimized Aerofoils
Optimizer: NSGA-II
Initial Population:
40 reversible aerofoils
Test Functions
Extended Population
Non dominated sorting + Crowding distance= Pareto Front
Next generation
10 generations





- XFoil was used as test function in the standard optimization

- To reduce the computational effort, LSM and ANN meta-models were developed

XFoil (MOEA)

SM : LSM, ANN
Single level framework

SM : LSM, ANN
Bi- level framework

Least square method (LSM)

The fitness function was approximated using a second-order polynomial response surface.

$$
\begin{aligned}
O = \zeta_0 + \zeta_1 F_1 + \zeta_2 F_2 + \ldots + \zeta_s F_s + \\
\zeta_{1,1} F_1^2 + \zeta_{2,2} F_2^2 + \ldots + \zeta_{s,s} F_s^2 + \\
\zeta_{1,2} F_1 F_2 + \ldots + \zeta_{s-1,s} F_{s-1} X_s + q
\end{aligned}
$$

The polynomial quantify the relation between the objectives vector (*O*) and the factors (*F*).

A least square method fit approach enables the estimation of the polynomial regressors (ζ).

Artificial Neural Network (ANN)

XFoil (MOEA)

SM : LSM, ANN
Single level framework

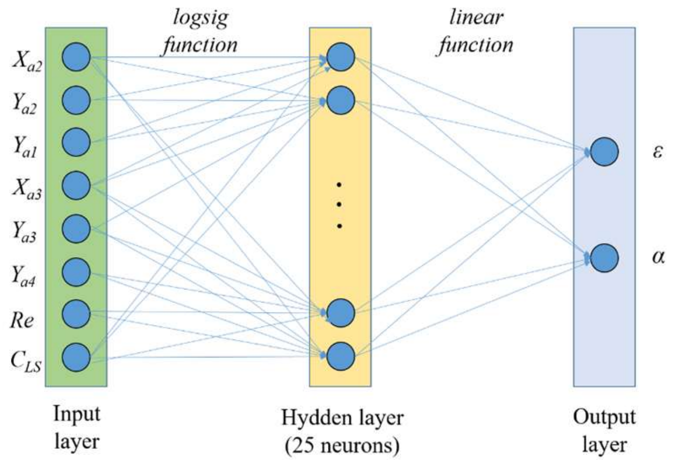
SM : LSM, ANN
Bi- level framework

LSM

Artificial Neural Network (ANN)

Multi-layer perceptron

One hidden layer,
25 neurons



ANN was trained using a Bayesian optimization algorithm, randomly initializing weights and biases between 1 and -1

XFoil (MOEA)

SM : LSM, ANN
Single level framework

SM : LSM, ANN
Bi- level framework

Single level framework

It's also called No evolution control (NEC) approach

The SMs are used in the MOOP framework without any assessment against the original fitness function

DOE → SM training → NSGA-II

In the simple-level approach the optimization is Entirely driven by the SMs

Bi-level framework

XFoil (MOEA)

SM : LSM, ANN
Single level framework

SM : LSM, ANN
Bi- level framework

Single level framework

DOE

SM training

NSGA-II

Bi-level framework

The Bi-level framework advocates the use of fitness function during EA process

Two stage approach:

- a number of solutions are produced and evaluated using the SM.
- The best solutions are then evaluated with the original fitness function to enrich the sampling data set from which the SMs are derived

DOE

SM training

NSGA-II

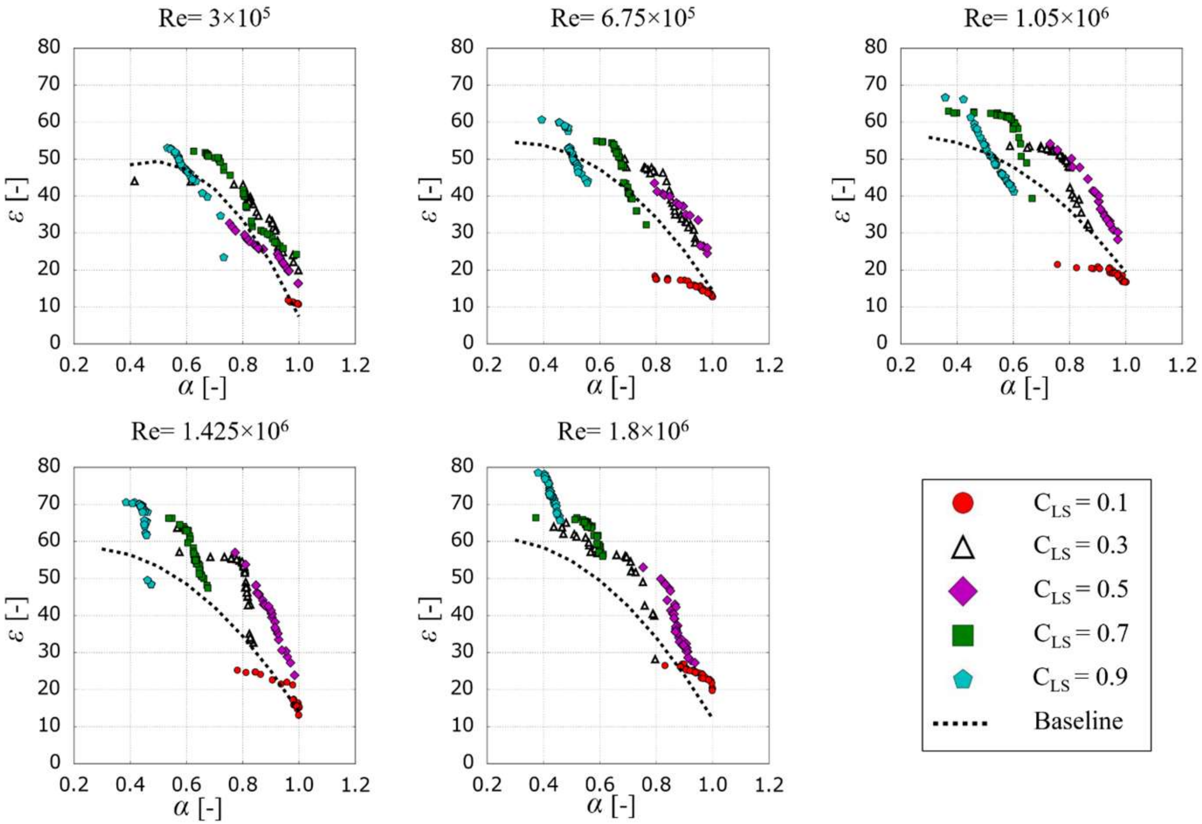
XFoil test

New samples

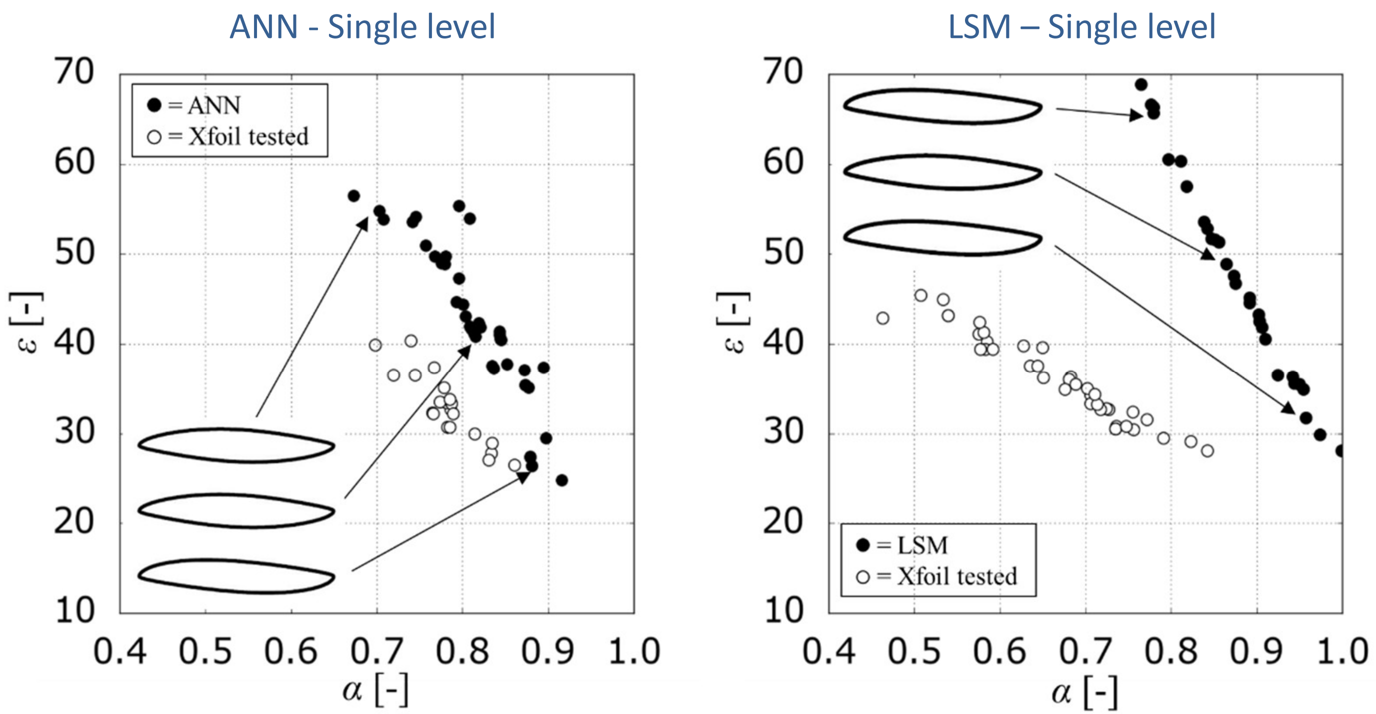
The standard MOEA results are illustrated. The selected objective function was based on XFoil.

The dotted line is the initial frontier. The optimization technique should move this imaginary frontier toward higher efficiencies and stall margins.

The results for all *Re* and C_{LS} combinations of the text matrix after 10 generations are shown.



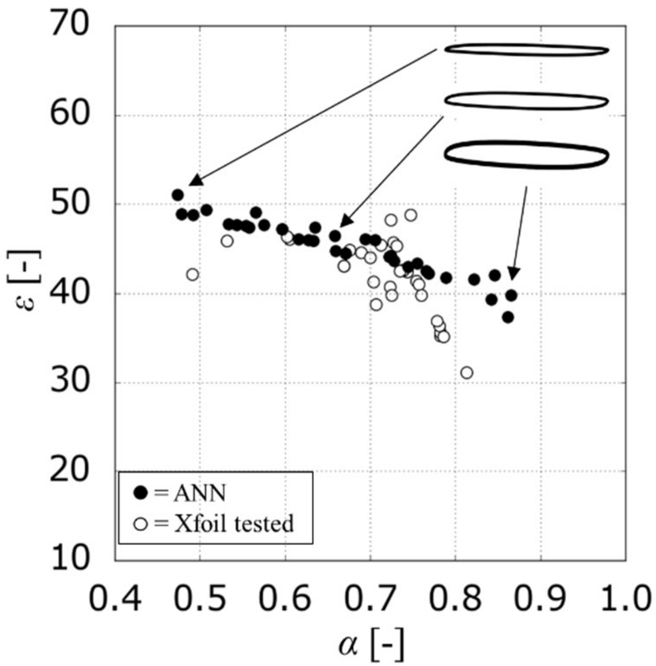
MOOP was solved using NSGA-II algorithm assisted by developed meta-models using the single level approach



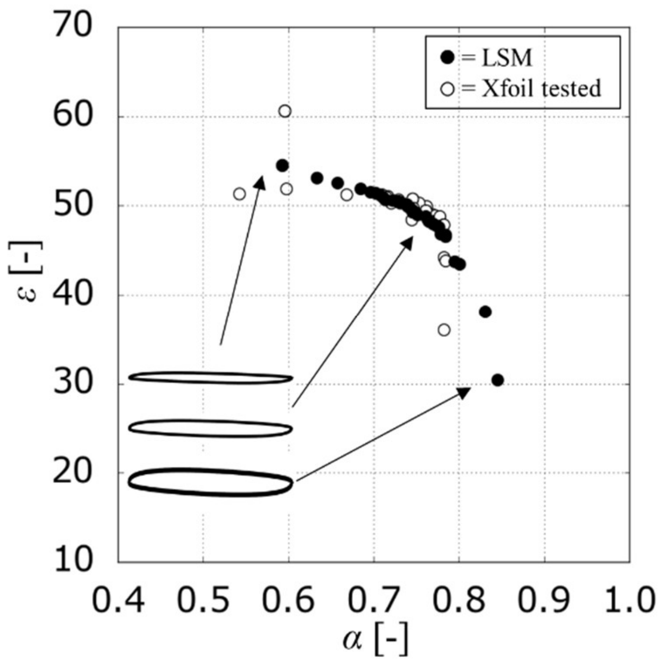
The figure shows the results of the final iteration loop for the combination Re=1.05×10^6, C_{LS}=0.5

Irrespective to the SM used, aerodynamic performance predictions are in good agreement with XFoil predictions. The aerofoil flow physics is well represented, in both SM-based optimization, by the change in the airfoil geometry

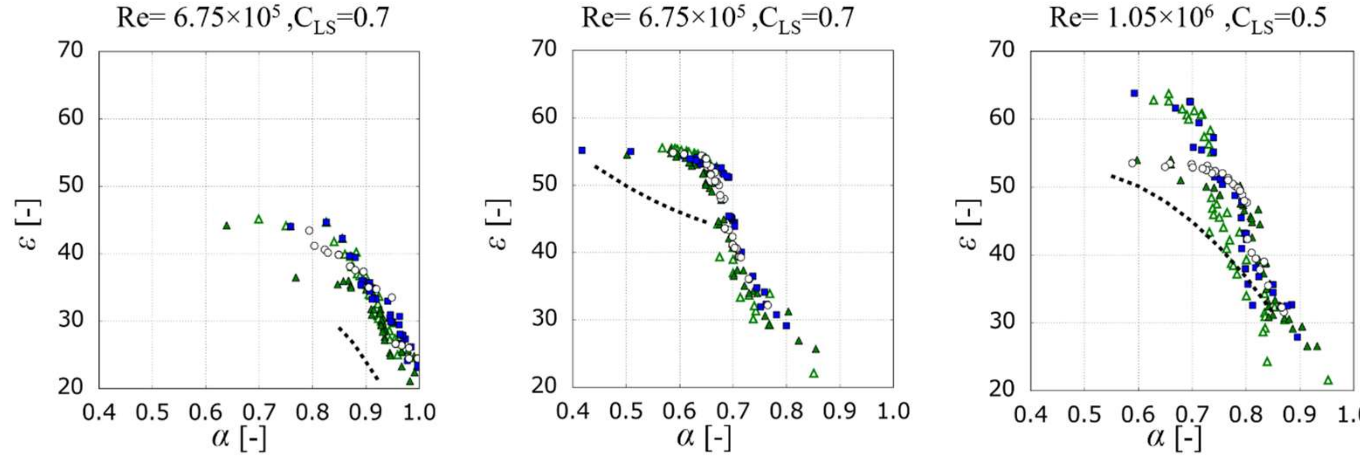
ANN - Bi level

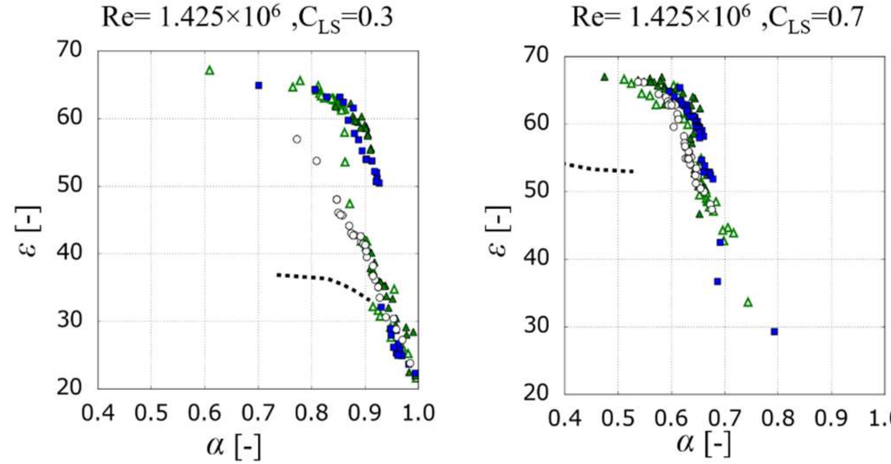


LSM – Bi level

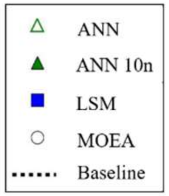


These results give at a glance the indication of the quality of SMs assisted optimization implemented in the Bi-level test-bed, using half of the computational effort required by the standard one



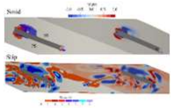


Re\C$_{LS}$	0.1	0.3	0.5	0.7	0.9
3×10^5					
6.75×10^5		x		x	
1.05×10^6			x		
1.425×10^6		x		x	
1.8×10^6					



Part 2: Case Studies and Lesson Learnt on ML and Fans

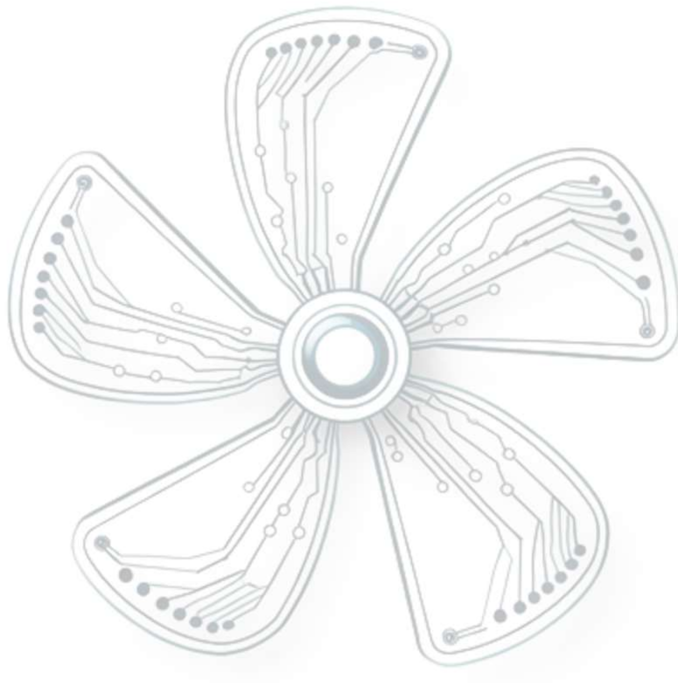
Surrogate-based optimization of truly reversible blade profiles for axial fans



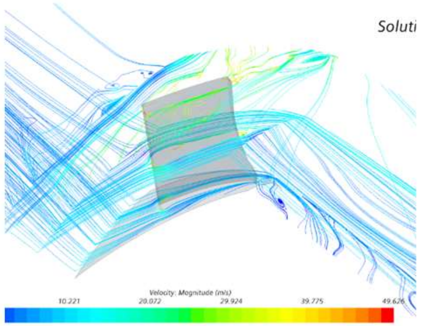
Machine-learning clustering methods applied to detection of noise sources in low-speed axial fan

A multidimensional extension of Balje chart for axial flow turbomachinery using artificial intelligence-based meta-models

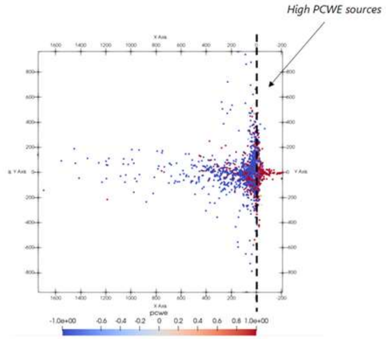
Lesson learnt & practical tips



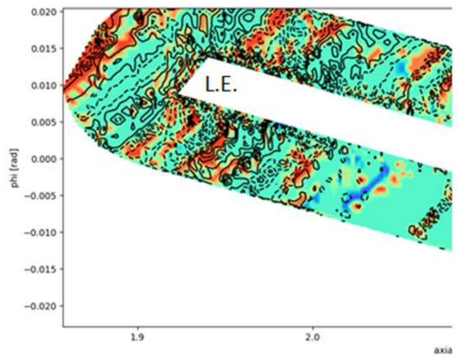
High fidelity numerical simulation



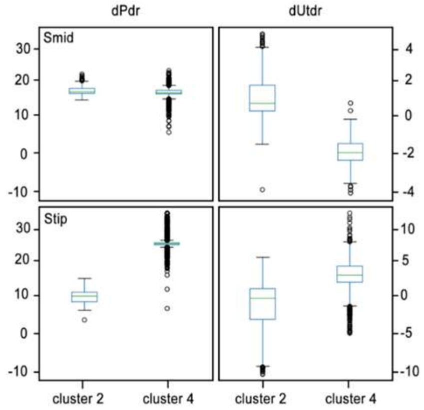
Dimensionality reduction Latent projection



Algorithm selection optimization



Statistical analysis of clusters



Raw data

EDA

Unsupervised learning

Distilled knowledge

Tieghi, L., Becker, S., Corsini, A., Delibra, G., Schoder, S., & Czwielong, F. (2023). Machine-learning clustering methods applied to detection of noise sources in low-speed axial fan. Journal of Engineering for Gas Turbines and Power, 145(3), 031020.

LES simulations carried out in StarCCM+

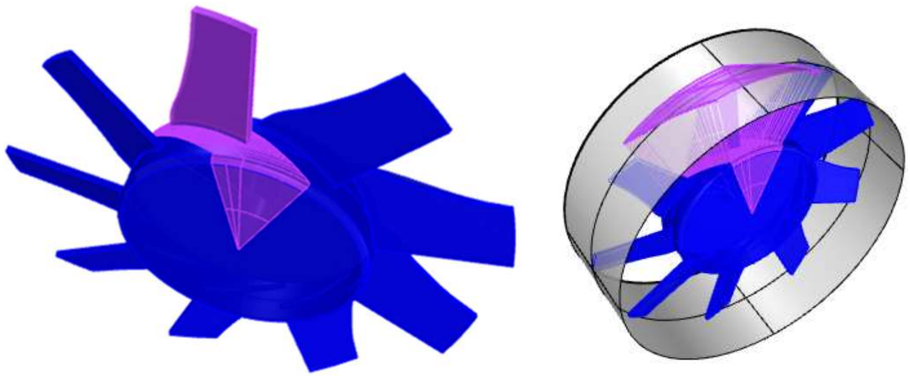
The geometry represented a ducted inlet – free outlet test rig

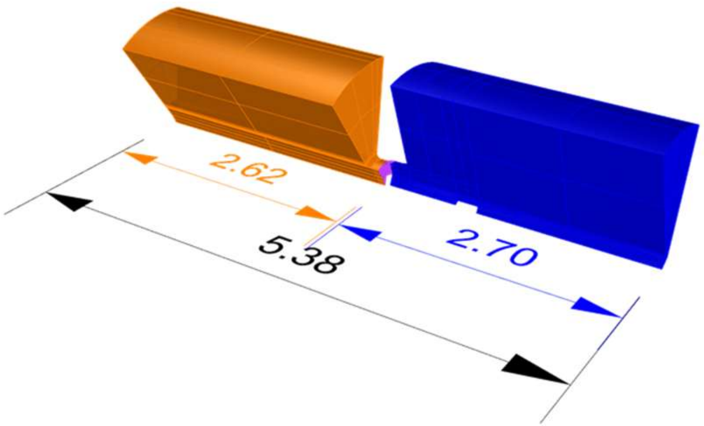
The inlet and outlet planes are located 5 diameters up- and downstream of the rotor region

The total domain length is 10.8D

Axial fan geometry and operating points

Rotational speed	1486	rpm
Hub diameter	250	mm
Tip diameter	497	mm
Casing diameter	500	mm
Tip clearance	1.5	mm
Volumetric flow rates	0.9 – 1.09 – 1.2	m^3/s
Number of blades	9	-





View of the fan and scheme of the domain (meters)

The PCWE model solves the acoustic wave propagation in the time domain

$$\frac{1}{c_0^2}\frac{D^2\phi^a}{Dt^2}\,\nabla\cdot\nabla\phi^a - = -\frac{1}{\rho_0 c_0^2}\frac{Dp^{ic}}{Dt}$$

Source term

Scalar acoustic potential

$$\frac{D}{Dt} = \frac{\partial}{\partial t} + \bar{u}\cdot\nabla$$

If the mesh is rotating, the substantial derivate in the source term is corrected by the rotational velocity

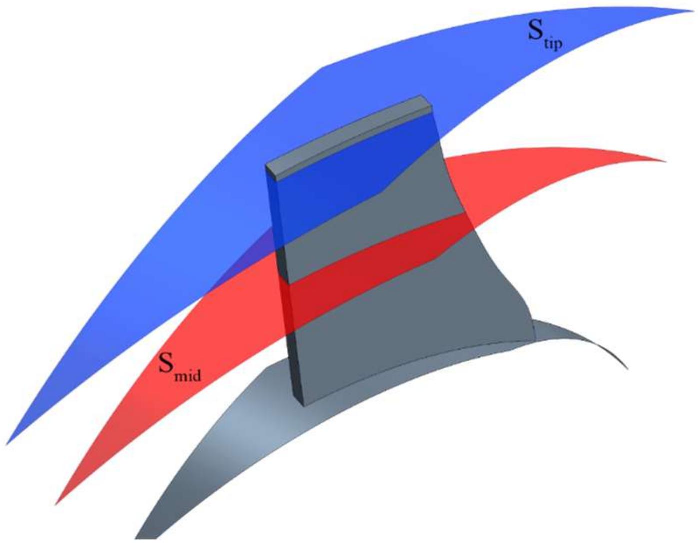
The aeroacoustic source term of this equation is the substantial derivative of the incompressible flow pressure p^{ic}

A

Exported during runtime computations with a 1000 Hz frequency

Very few clustering algorithms can treat million of data, therefore the analysis is carried out on a reduced dataset

It is obtained by generating two sampling cylindrical surfaces in the rotor region, S_{mid} and S_{tip}, at 50% and 95% of the blade span



Sampling surfaces for reduced clustering: S_{tip} (R = 0.236 m) and S_{mid} (R= 0.125 m)

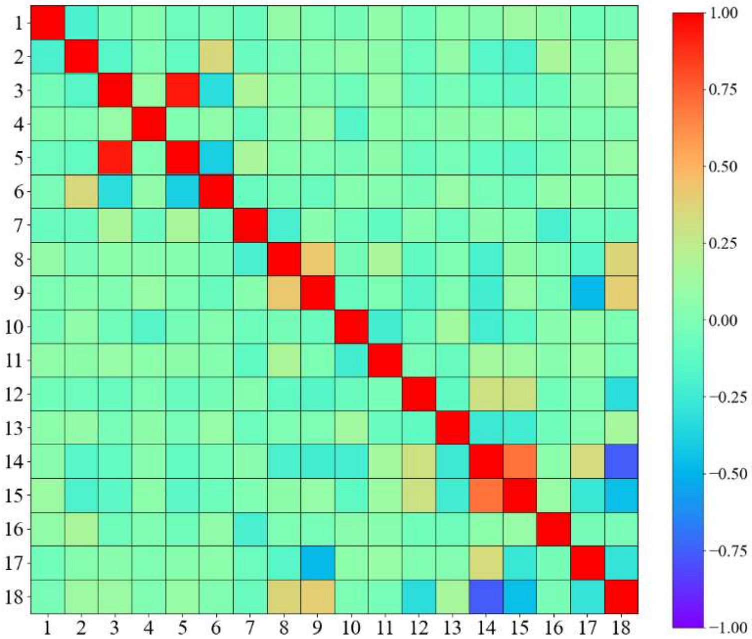
Exported Features

Feature number	Feature
1	PCWE sources
2	P
3	k
4-6	U_i
7-9	$\partial P/\partial x_i$
10-18	$\partial U_i/\partial x_j$

Different strategies were investigated to explore the possibility of reducing the dimensionality of the dataset

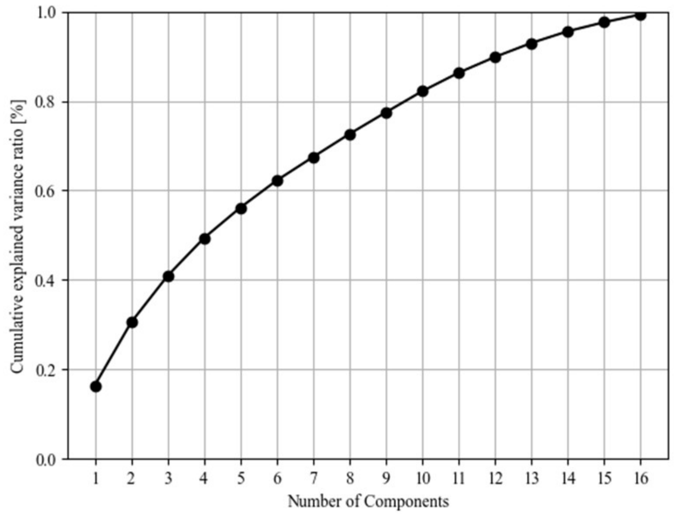
Correlation analysis was exploited to understand the statistical significance of the features

PCA and t-SNE algorithms were tested for feature reduction



Correlation matrix heatmap for input data

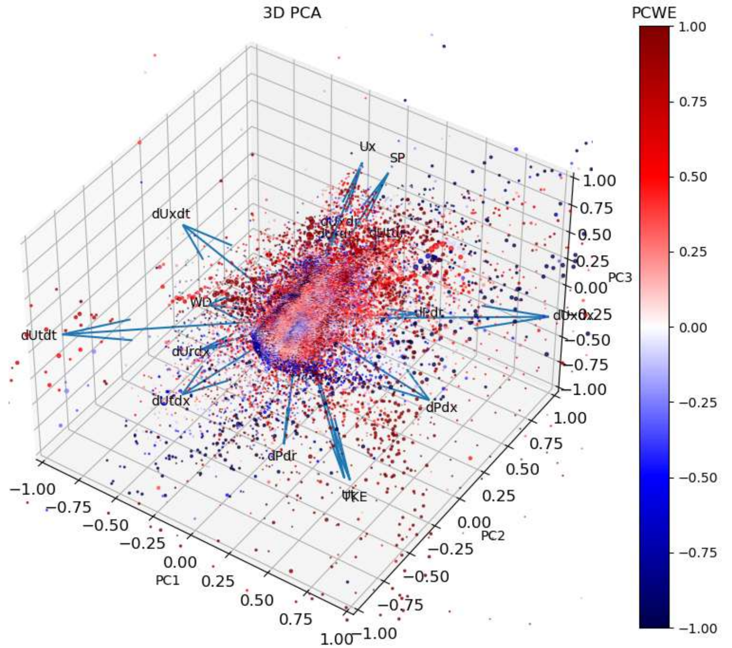
Feature number	Feature
1	PCWE
2	P
3	k
4-6	U_i
7-9	$\partial P/\partial x_i$
10-18	$\partial U_i/\partial x_j$



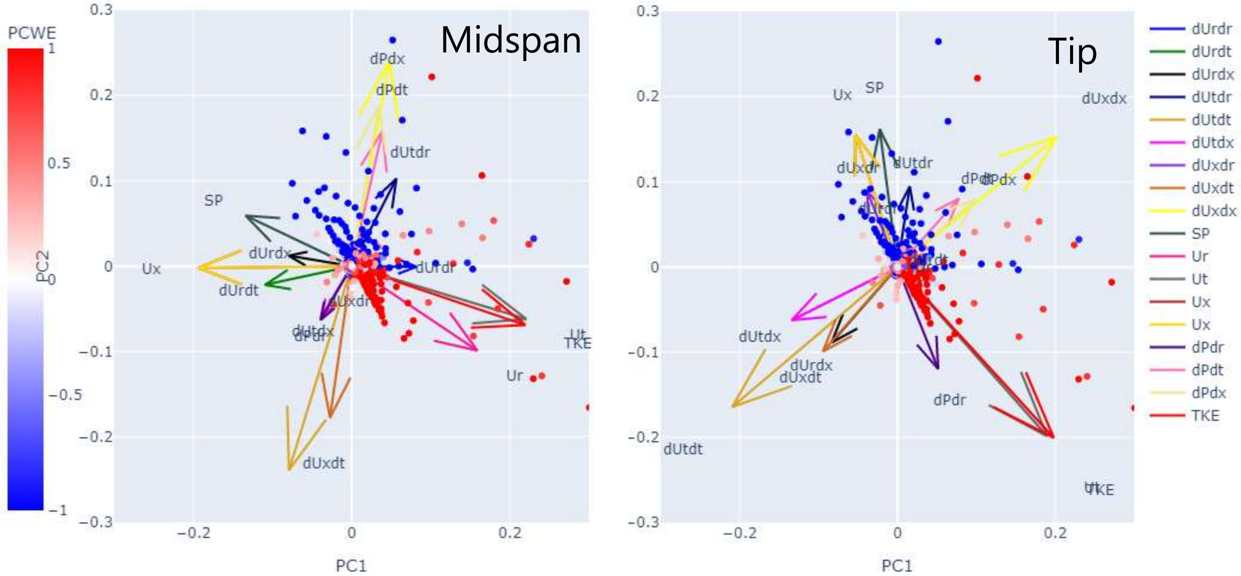
Explained variance as a function of the number of components for 5 blade revolutions for the whole dataset

Plotting samples on the two principal components arise patterns in data:

- Axial velocity U_x is aligned with -x direction on S_{mid} and with y direction on S_{tip} -> PCWE value is directly correlated with U_x, this separation is not dependent upon U_x.
- At S_{mid} PCWE sources are dependent on dU_x/dt and dU_t/dr, -> the work distribution along the blade span is responsible for this term.
- At S_{tip} the PCWE distribution is dependent on U_x, static pressure SP, dU_i/dr and pressure derivative with respect to radial direction dP/dr.

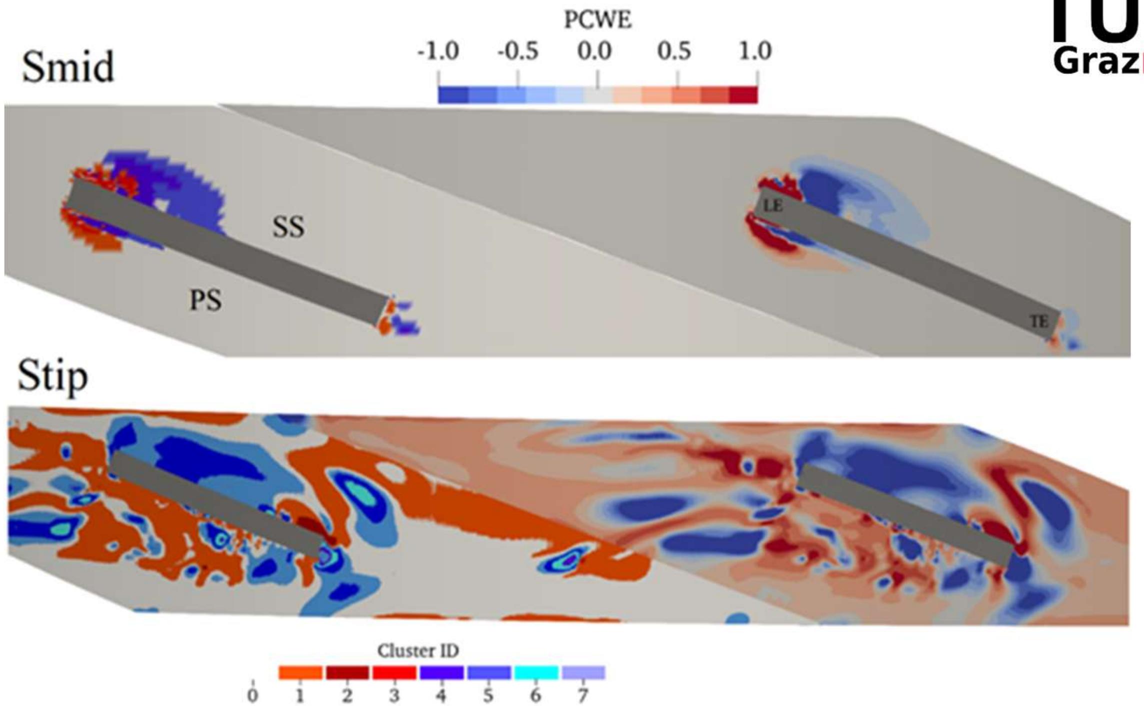


Projection of the training dataset on the PCA basis on the first three principal components



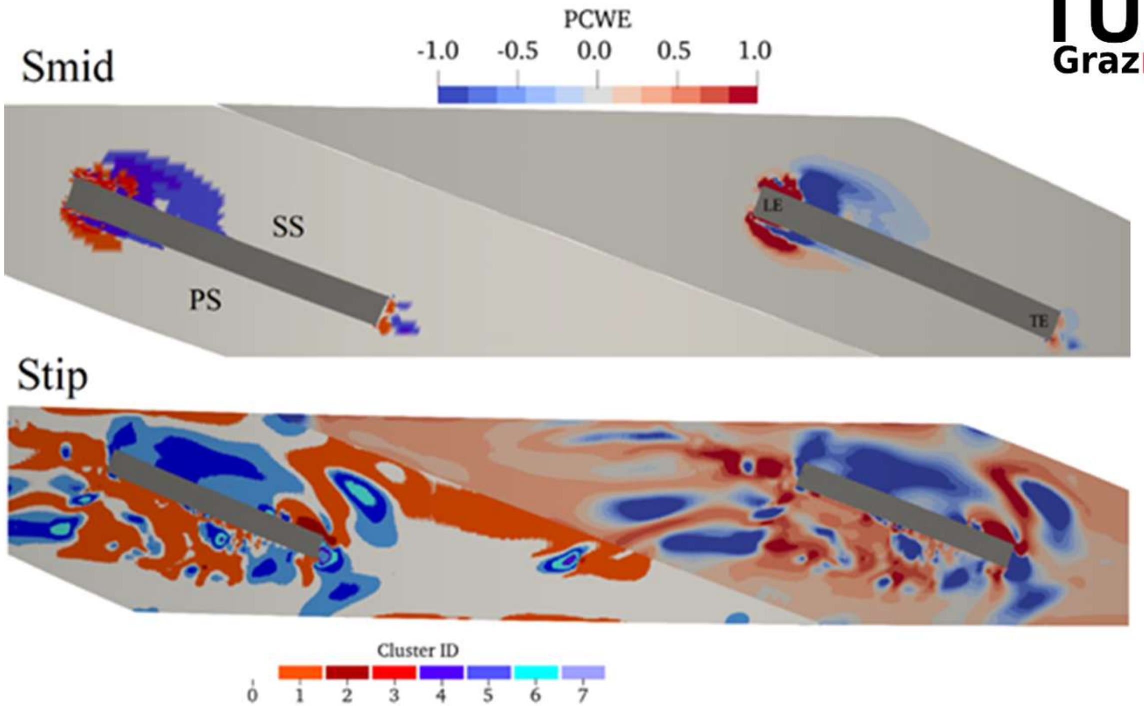
Projection of Smid and Stip training dataset on the PCA basis on the first two principal components

- Likelihood of the clustering algorithms with PCWE distribution was evaluated using an image similarity algorithm
- The highest likelihood scores (>80%) were observed in the kMeans-based algorithms with number of clusters > 20 and a reassignment ratio of 0.05
- Similar results were achieved by the GM algorithm, with 7-8 mixtures and a full covariance computation
- Results from DBScan, although partially comparable with the other two algorithms in Smid (likelihood score = 73%), were extremely worse in the Stip region.



Comparison between the GM results with number of mixtures = 8 and full covariance matrix (left) and normalized PCWE sources distribution (right) for midspan and tip sections.

- Likelihood of the clustering algorithms with PCWE distribution was evaluated using an image similarity algorithm
- The highest likelihood scores (>80%) were observed in the kMeans-based algorithms with number of clusters > 20 and a reassignment ratio of 0.05
- Similar results were achieved by the GM algorithm, with 7-8 mixtures and a full covariance computation
- Results from DBScan, although partially comparable with the other two algorithms in Smid (likelihood score = 73%), were extremely worse in the Stip region.
- Regions that show high positive PCWE levels, correspond to the cluster ID 1,2 and 3.
- Negative PCWE can be observed in the IDs 4-7
- Accurate prediction in the regions with high magnitude of PCWE sources, whereas less accurate in presence of levels that are gradually close to zero.
- In the Smid section, PCWE sources at the leading edge are correctly reproduced, apart from a region on the suction side at the 20% of blade chord, that is incorrectly labeled as background, corresponding to ID=0

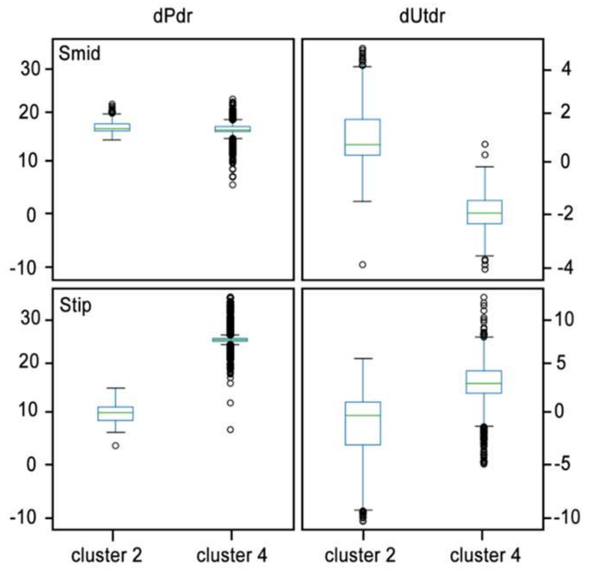


Comparison between the GM results with number of mixtures = 8 and full covariance matrix (left) and normalized PCWE sources distribution (right) for midspan and tip sections.

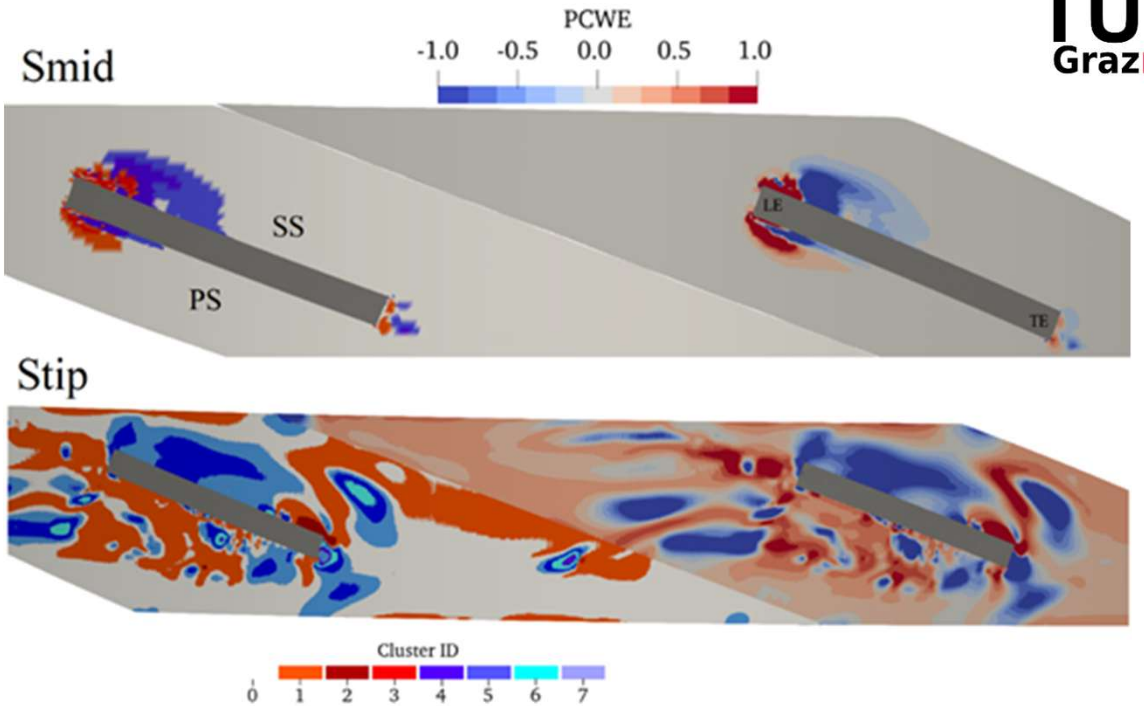
Cluster 2 and 4 are compared with respect to significant features

In so doing, the contribution of the single features to the source level can be highlighted and further exploited

For example, of dP/dr are quite similar for both clusters (in fact dP/dr had no correlation with PCWE) while distributions of dU/dr are different



Distributions of scaled dP/dr and dUt/dr at midspan and tip surfaces for cluster 2 and cluster 4.

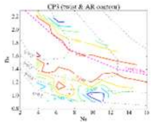


Comparison between the GM results with number of mixtures = 8 and full covariance matrix (left) and normalized PCWE sources distribution (right) for midspan and tip sections.

Part 2: Case Studies and Lesson Learnt on ML and Fans

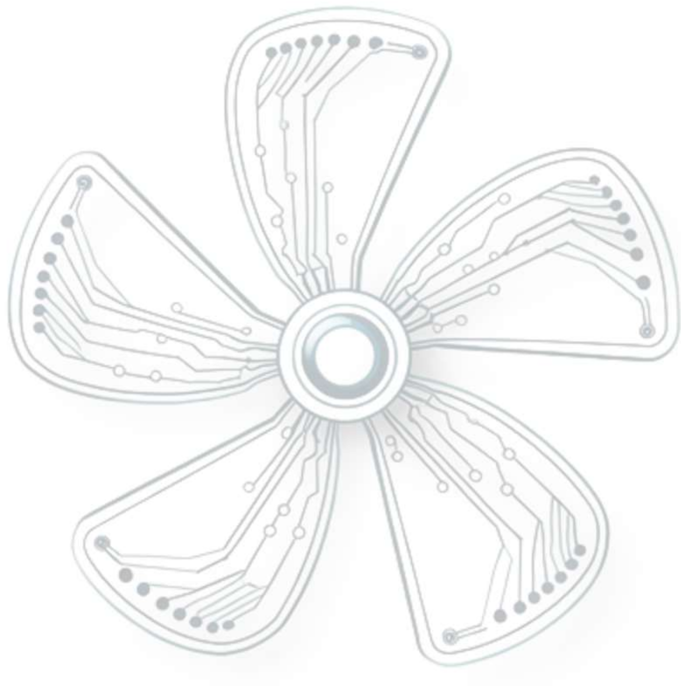
Surrogate-based optimization of truly reversible blade profiles for axial fans

Machine-learning clustering methods applied to detection of noise sources in low-speed axial fan



A multidimensional extension of Balje chart for axial flow turbomachinery using artificial intelligence-based meta-models

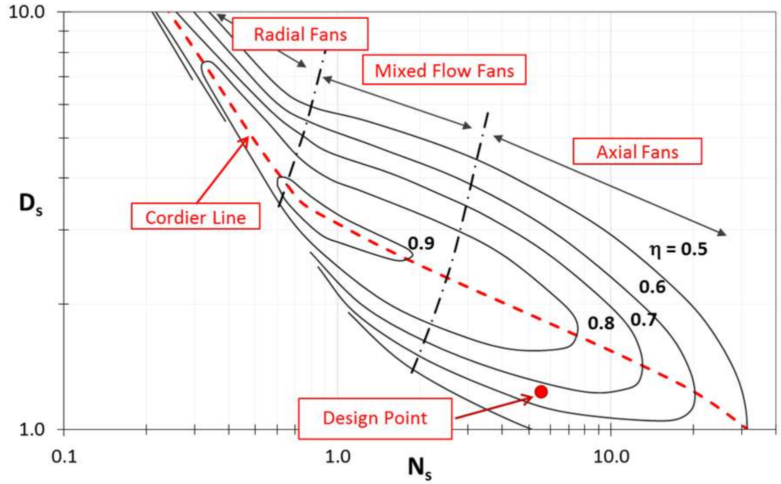
Lesson learnt & practical tips



Balje **standardized** the design process of turbomachinery

Design charts reported the efficiency as function of **Ns** and **Ds**

The **issue** regards the **dimensionless** of the considered parameters



- Aim of the following work is the **exploration of axial fan design space** aiming at derive a set of **multidimensional Balje charts,** where the **main geometric and operational parameters are taken into account** in addition to the specific speed and diameter

Angelini, Corsini, Delibra and Tieghi: A Multidimensional Extension of Balje Chart for Axial Flow Turbomachinery Using Artificial Intelligence-Based Meta-Models. J. Eng Gas Turbine and Power 2019. GTP-19-1439

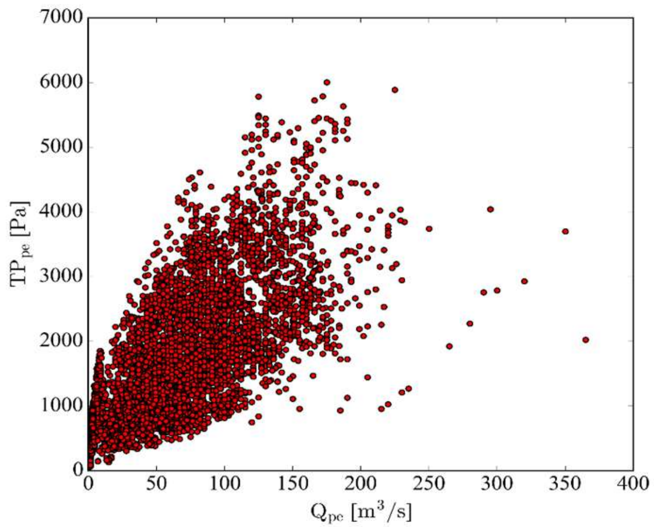
An enhanced in-house software has been exploited during the exploration.

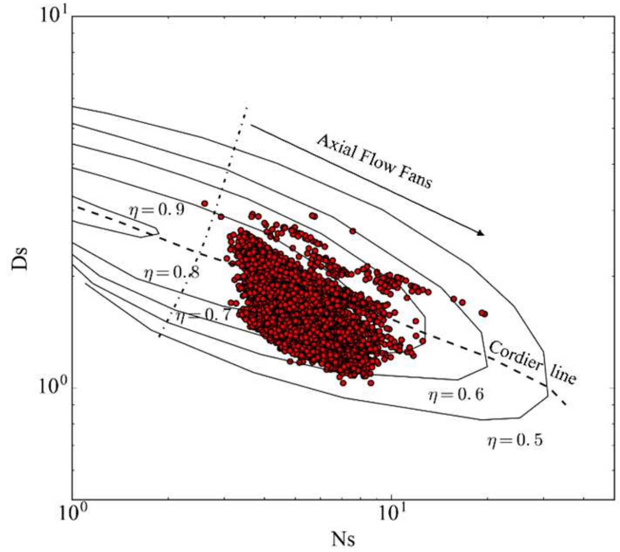
A Hyper-surface of solutions of axial flow fans performance has been derived.

The geometric and operative ranges of the fan tested are shown in the table:

Shroud diameter	0.2 ÷ 2.5 m
Hub-to-tip ratio	0.25 ÷ 0.75
Number of blades	4 ÷ 16
Hub pitch disposition	15 ÷ 60 deg
Mid-span solidity	0.25 ÷ 1.15
Twist	5 ÷45 deg
RPM	600 ÷ 3600

Number of simulations: 7313





The population was initially analyzed by Principal Components Analysis (PCA).

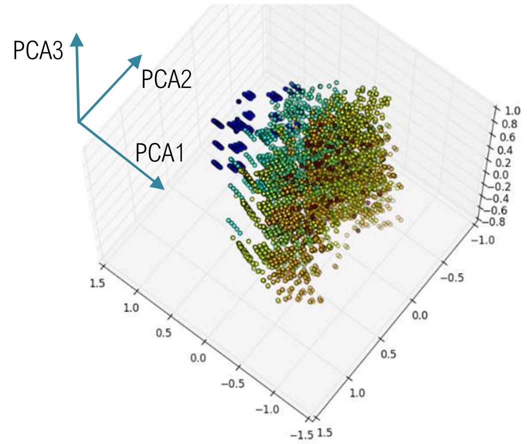
PCA reduces the dimensionality while retaining most of the variation in the data set.

PCA is applied to the main representative fan parameters:

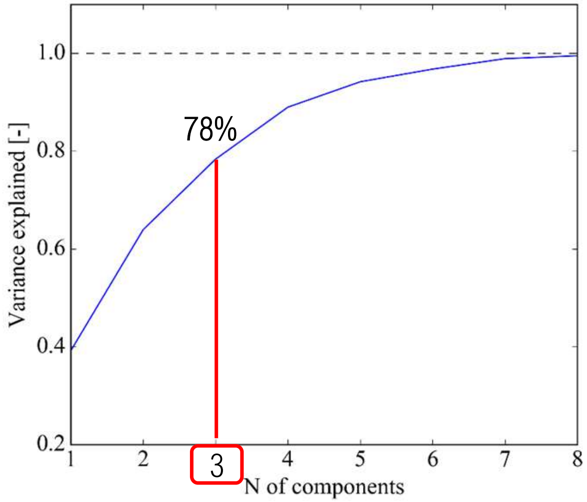
- Tip Diameter (D_t)
- Solidity
- Aspect Ratio (AR=h/l)
- Hub-to-tip ratio (HR)
- Twist
- Blade number (z)
- Rotational speed (RPM)
- Flow rate (Q), Pressure ratio (P)

First 3 components account for the 78% of data-set variability (elbow method)

PCA transformation



Elbow chart



Following analysis required the use of **PLS**.

Data-set variables are divided in **input** and **output** variables.

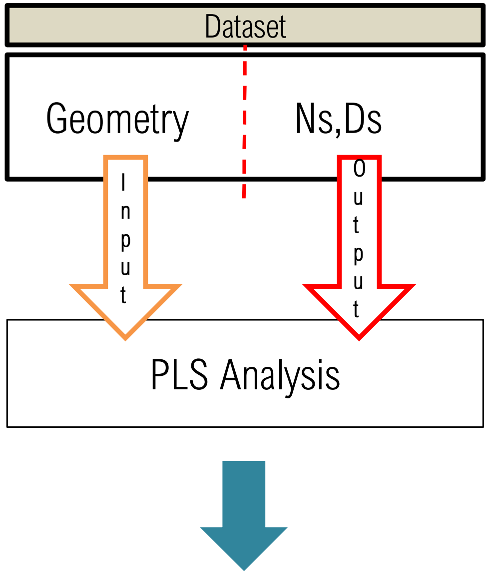
PLS creates orthogonal score vectors by **maximizing** the **covariance** between these two sets of variables.

Ns and **Ds** are considered **output** variables of PLS process:

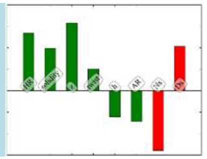
$$Ns = \frac{RPM \cdot \sqrt{Q}}{P^{\frac{3}{4}}}, \qquad Ds = \frac{Dt \cdot P^{\frac{1}{4}}}{\sqrt{Q}}$$

The fan **geometric features** are **input** of PLS analysis.

The aim is finding the relation between these geometric variables and Ns, Ds.



The effect exerted by input on output is quantified computing loading vector



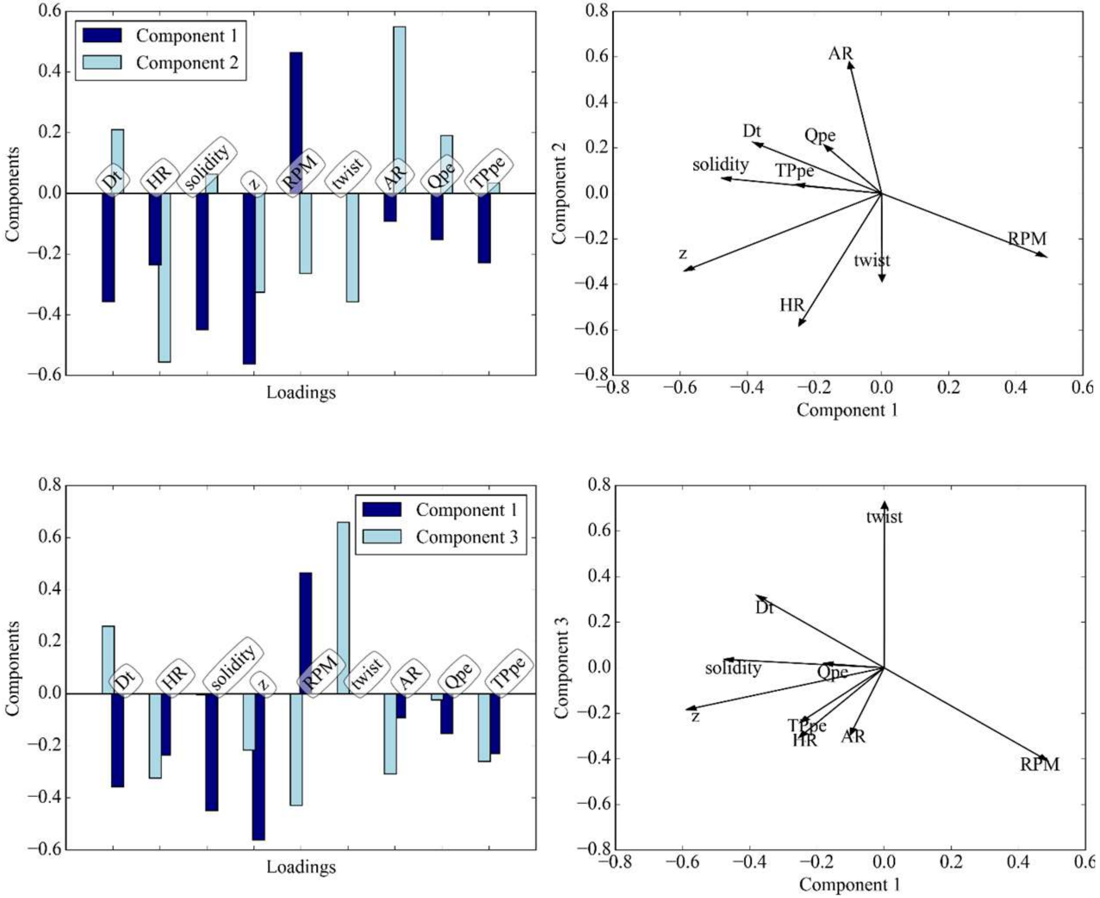
PCA loadings contribution to 1st and 2nd, and 1st and 3rd components are reported.

Dt, solidity, z and RPM have the higher magnitude for the 1st component.

AR and HR have significant loading on 2nd component, positive and negative respectively.

The vector diagrams show that HR is completely uncorrelated with Dt and RPM.

Twist has the largest loading on 3rd component, resulting strictly related to blade loading level.



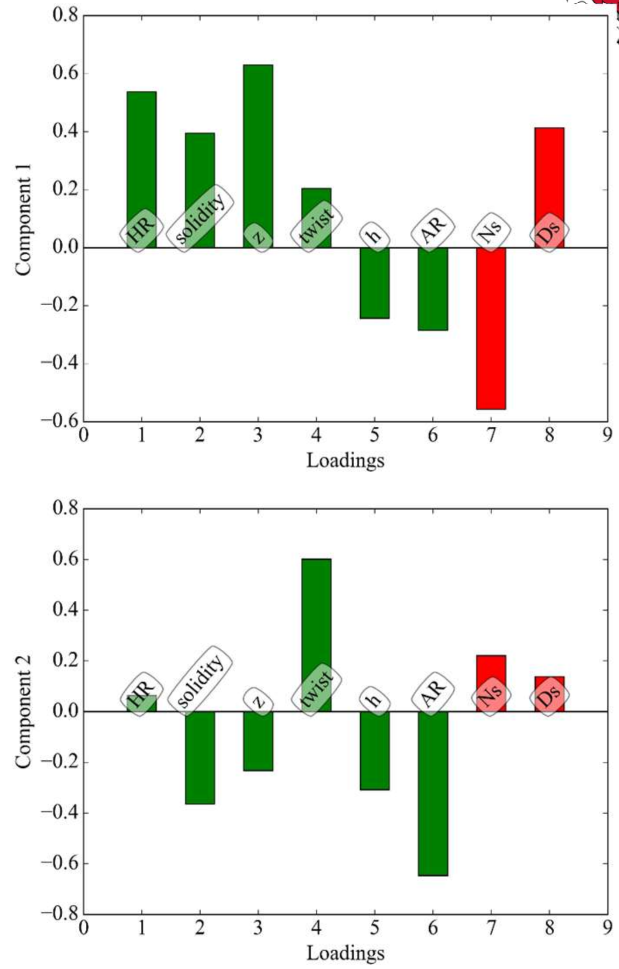
PLS loading vector on 1st component shows the relationship between HR, solidity and z and their influence on Ns and Ds

High values of these parameters determine increases in Ds while decrease Ns

A significant relation of twist angle and aspect ratio on Ns and Ds is highlighted

Twist results directly proportional to Ns, Ds, while the AR has an opposite trend resulting indirectly proportional

<u>The relationship between fan geometry and Ns, DS will define 3 **combined parameters** (**CP**) used to better drive the exploration of Balje chart.</u>



PLS results allow defining 3 composed parameters (CP)

CPi values define two-dimensional contour graphs on the Ns-Ds plane

CP_1 groups HR and sigma because are measure of two different “solidities”

HR and z was selected according to their loading values in CP_2

CP_3 grouping AR and twist is a measure of the blade global load

First Composed Parameter

hub ratio　　solidity

$$CP_1 = \frac{w_{HR,1} \cdot HR + w_{\sigma,1} \cdot \sigma}{abs\left(w_{HR,1} + w_{\sigma,1}\right)}$$

Second Composed Parameter

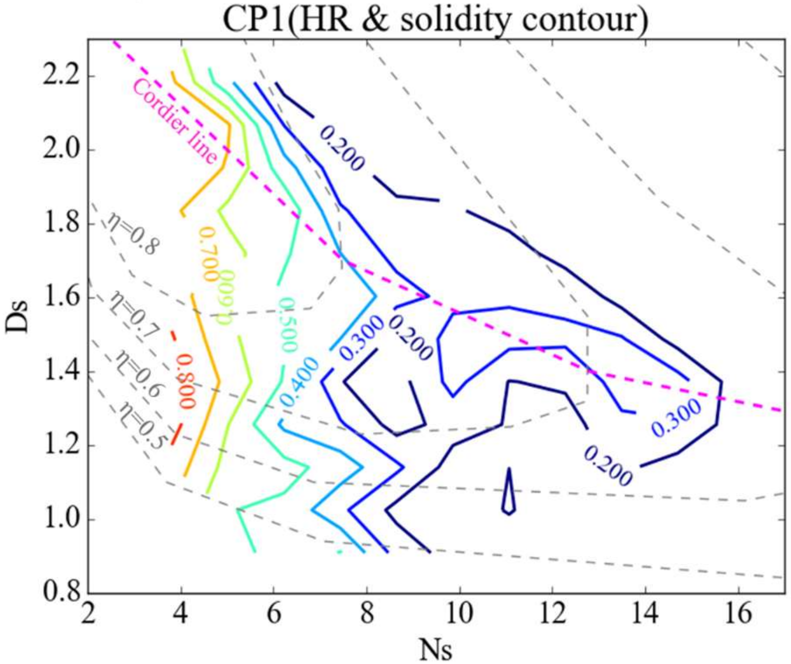
hub ratio　　blade count

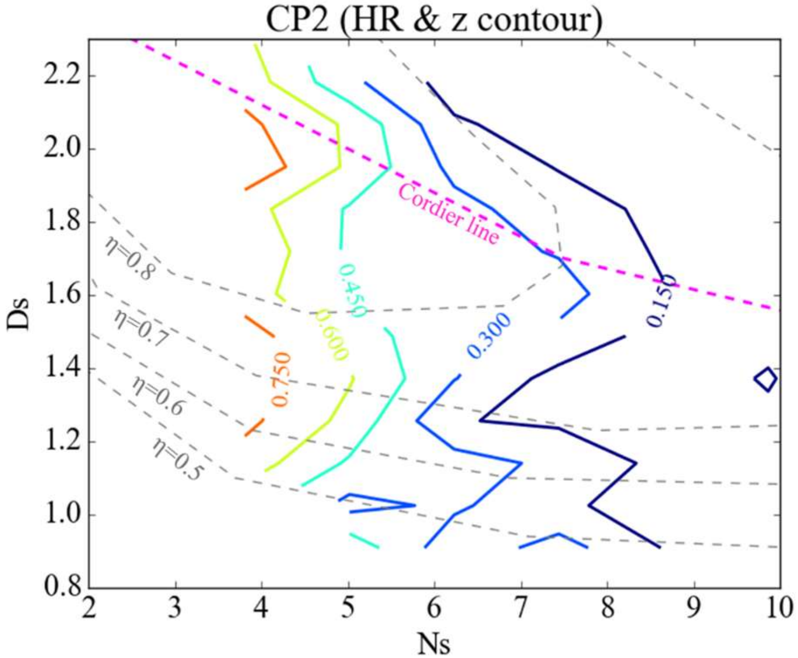
$$CP_2 = \frac{w_{HR,1} \cdot HR + w_{z,1} \cdot z}{abs\left(w_{HR,1} + w_{z,1}\right)}$$

Third Composed Parameter

blade twist　　aspect ratio (h/l)

$$CP_3 = \frac{w_{twist,1} \cdot twist + w_{AR,1} \cdot AR}{abs\left(w_{twist,1} + w_{AR,1}\right)}$$





CP_1 values decrease moving through higher Ns values while high values are confined between Ns=(4-6).

CP_2 contour lines have vertical trend with lower values at higher Ns.

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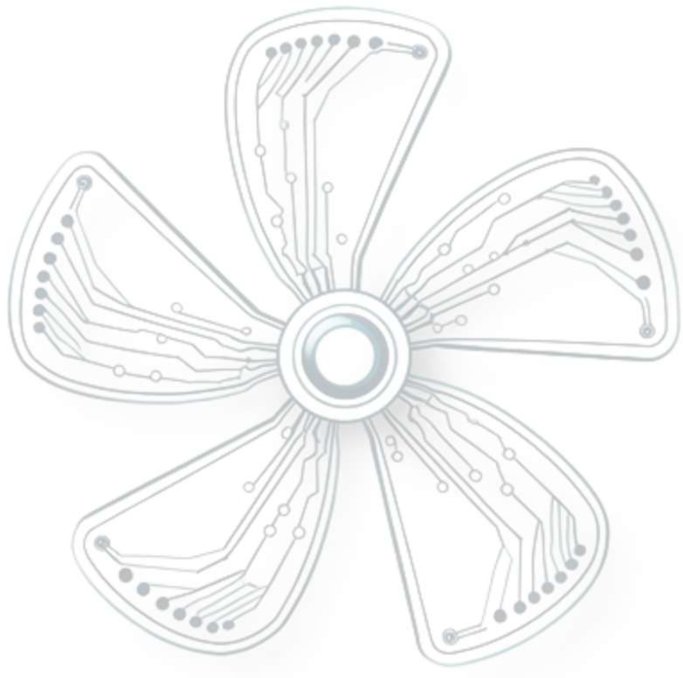
A multidimensional extension of Balje chart for axial flow turbomachinery using artificial intelligence-based meta-models

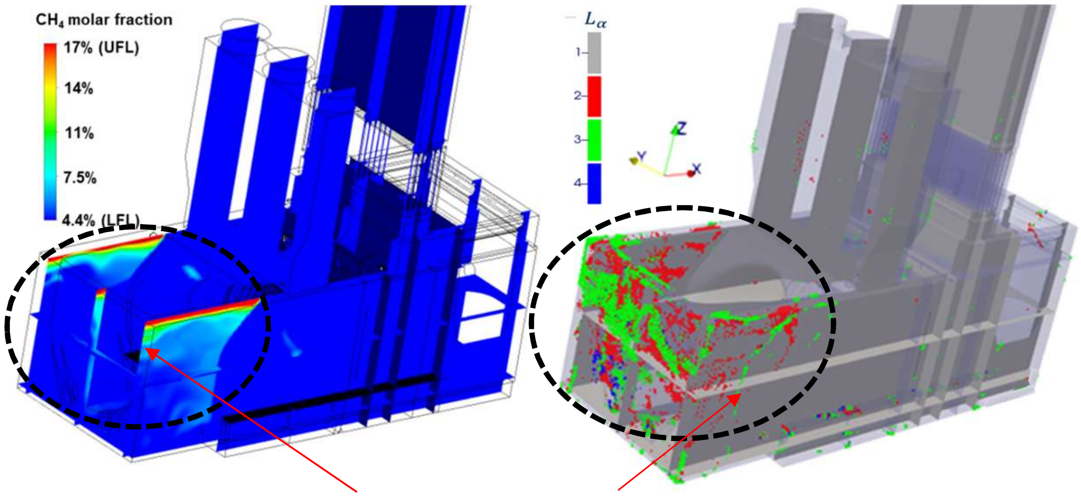
Lesson learnt & practical tips



Data handling and feature preprocessing

With respect to standard ML practice, turbomachinery ML presents additional challenges:

- <u>Sparsity of data:</u> Datasets cannot always be populated as desired due to practical limitations.
- <u>High dimensionality but…:</u> Many engineering problems suitable for ML cannot be easily linearized, leading to an increased number of variables and greater model complexity.
- <u>… less is more:</u> Reducing model complexity—including input features—offers significant advantages in terms of interpretability and performance.
- <u>Peculiarity of features:</u> The statistical distributions of variables rarely follow standard forms, often exhibiting high skewness and kurtosis, which complicates data handling.
- <u>Data availability:</u> ML requires that all input features be available. Before starting, we should ask: "Will this input feature always be available?" Consider issues like varying sampling frequencies or unsteady data.

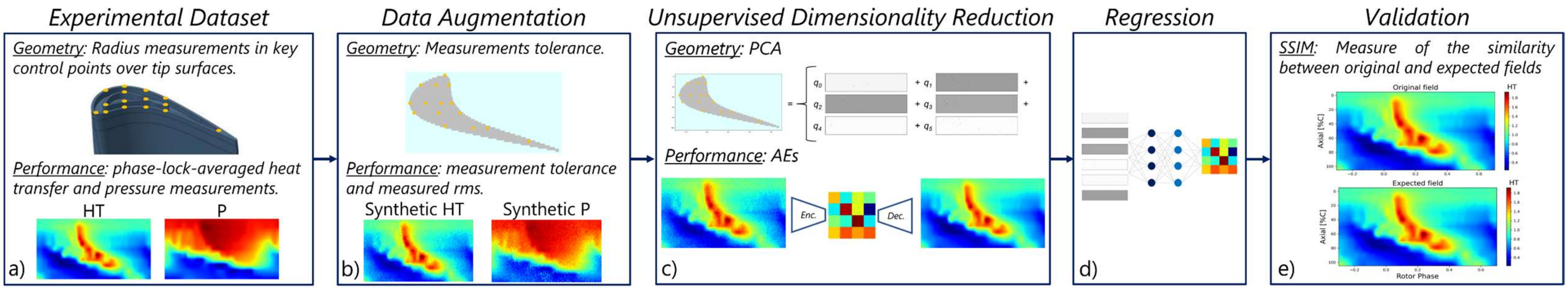


Poorly ventilated region upstream inlet plenum

Corsini, A., Delibra, G., Giovannelli, M., Lucherini, G., Minotti, S., Rossin, S., & Tieghi, L. (2020, September). Prediction of Ventilation Effectiveness for LM9000 Package With Machine Learning.

Data handling and feature preprocessing – Advanced tips

- PCA is your best friend: Principal Component Analysis (PCA) and other dimensionality reduction techniques are highly recommended during the preliminary stages of ML model development.
- Coordinate system transformation: Model generalization can often be improved by applying standard turbomachinery coordinate transformations (e.g., cylindrical coordinates).
- Feature normalization/standardization: Standard ML normalization techniques may not perform well, particularly with CFD data. Local normalization tends to yield better results.
- Outliers are not always bad: While outliers are often discarded in standard ML practice, this is not advisable in turbomachinery ML. Outliers can represent critical localized phenomena (e.g., shocks, boundary layers) that are essential to model



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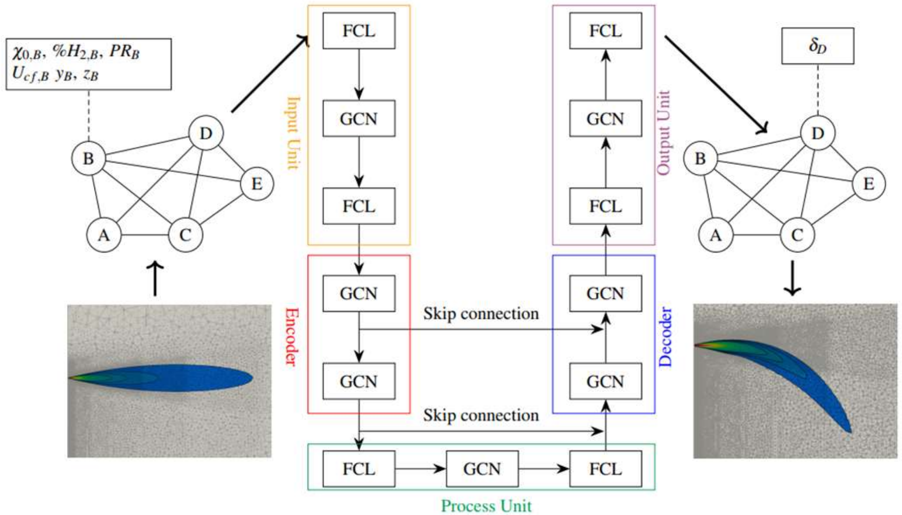
Model selection and implementation

- Don't overcomplicate model design: as long as the problem to solve is clearly formalized and input data makes sense, results should be sound even with "shallower" models.
- Implementation matters: even if differences are small, results may vary from implementation to implementation (e.g. Tensorflow, pyTorch, etc.)
- ANNs (+ PCA) are the bread and butter of TM ML algorithms: despite their known limitations, artificial neural networks can solve most of the supervised problems. PCA further helps retaining the correlations in the original dataset.
- Not all unsupervised models are feasible: the scalability of some clustering methods (e.g. hierarchical) often prohibits their application –> kMeans.
- Beware of boosting algorithms: boosting algorithms are tempting, however they generalization capability is poorer than we expect.
- Use ML models with caution: the limited extrapolation capability of the models require extra caution when applied to out-of-the-box scenarios.

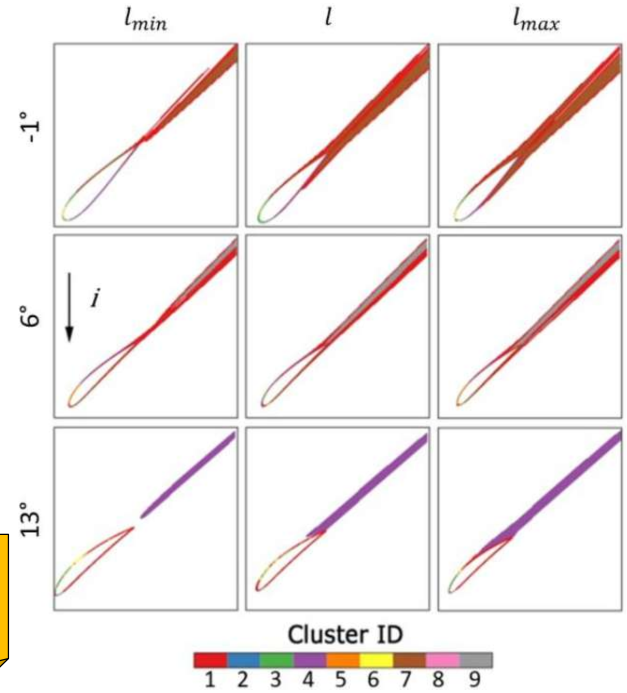


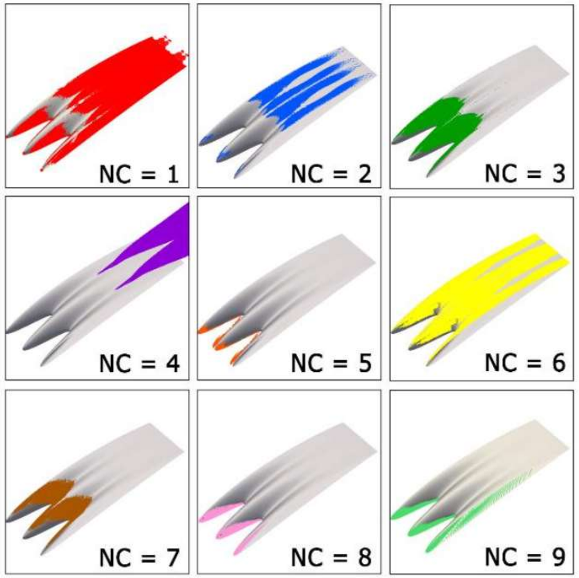
U-NET GCN for prediction of ventilated H_2 jets

Cerbarano, D., Tieghi, L., Delibra, G., Minotti, S., & Corsini, A. (2025). Modeling High-Pressure Hydrogen Gas Leakages With Graph Neural Networks. Journal of Energy Resources Technology, Part A: Sustainable and Renewable Energy, 1(3).

Model selection and implementation

- Advanced ML methods and TM-ML applications rarely go along: even if fascinating, complex and advanced methods (like physic informed algorithms) have limited applicability to real engineering problems. A difficulty of communication of the scopes between turbomachinery-ML users and ML experts exist!
- Follow a simplified design: it's more efficient to start with a limited number of features, reduced number of samples and a reliable (and fast to train) algorithm and then complicate the various aspects based on the desired scopes.
- Support your models with knowledge: it is easier to improve an existing model than to train from scraps. Use this at your advantage.
- If nothing works, check your data preprocessing: if the model performance are poor, look back at the exploratory data analysis and at feature preprocessing.





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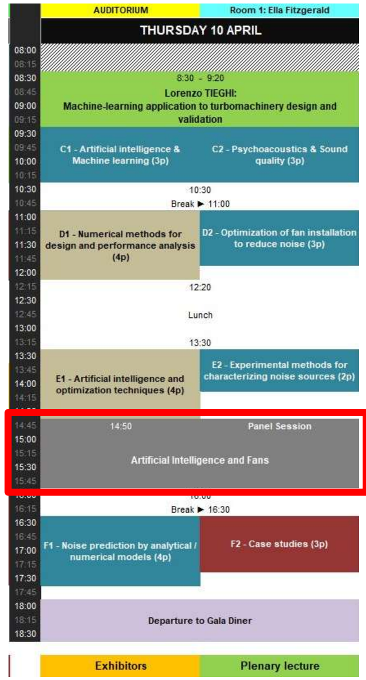
OUTLINE

- Part 1: Introduction to Machine Learning and Its Role in Fan Research (15 min)
- Part 2: Case Studies and Lesson Learnt on ML and Fans (30 min)
- Part 3: Conclusion & Q&A (10 min)

This afternoon @ 14:45 there will be a dedicated panel discussion regarding the use of AI in the fan industry.

Help us by taking a very short survey on your experience and thoughts – results will be discussed during the panel.

This panel brings together experts from **industry and academia** to explore the potential of AI, the hurdles we may face, and how reliable and impactful AI-driven methods can truly be.



10 Questions – completely anonymous

Scan the QR code with your smartphone camera to access the survey.
https://forms.gle/LPLME8k49pzNd6RX8

- AI & ML bring a **new research paradigm** to turbomachinery and fan applications.
- AI & ML can be applied at **various stages of a fan's lifecycle** – from speculative research aimed at uncovering hidden patterns in data, to optimization and validation processes, and finally, to supporting operation and maintenance policies.
- At this stage, **significant efforts are required to integrate AI and ML into industrial processes.**
  While isolated, highly effective applications exist, they are far from constituting a smart, intelligent system.
- **The role of the engineer and turbomachinery expert cannot be substituted:** physics must be incorporated either formally into the problem or through our supervision.
- With generative algorithms becoming predominant, it will be possible to achieve results in a matter of minutes, even without expertise in the field. However, this lack of expertise could be one of the main sources of **unreliability in ML.**
- ML and AI should be viewed as **helpful tools** to support our work as researchers and engineers, rather than as solutions for all problems.

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Research

Leverage the gap between ML research and ML-TM research

Create best practices, methods and standards to support the development of this discipline

Communication

Enhance exchange of ideas and opinion and create dedicated event for the discussion (a special thank to Fan conference)

Create open dataset and public database of fans (and TMs), to engage the engineering community and promote standardization

Industrialization

Promote the application of ML- and AI-based solutions in the workflow, with particular attention to the R&D phase

Expose the most limiting factors and obstacles to the development of this field.

Education

Introduce ML topics and applications to students and future engineers during the TM-related courses

Create specialized courses for TM expert, with a practical approach to the problem

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A WELL-FOUNDED CONCERN

Is AI the future of turbomachinery and fans?

“All models are wrong, but some are useful” – G. Box, 1976

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Is AI the future of turbomachinery and fans?

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THANK
YOU

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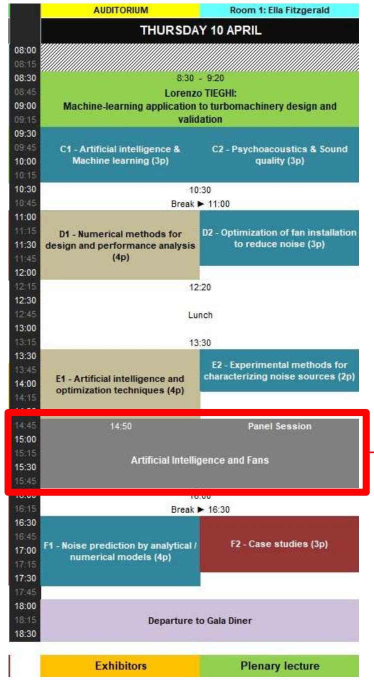

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