AVT-357 Research Workshop on “Technologies for future distributed engine control systems (DECS)”

Towards explainable artificial intelligence for centrifugal compressor operating conditions classification

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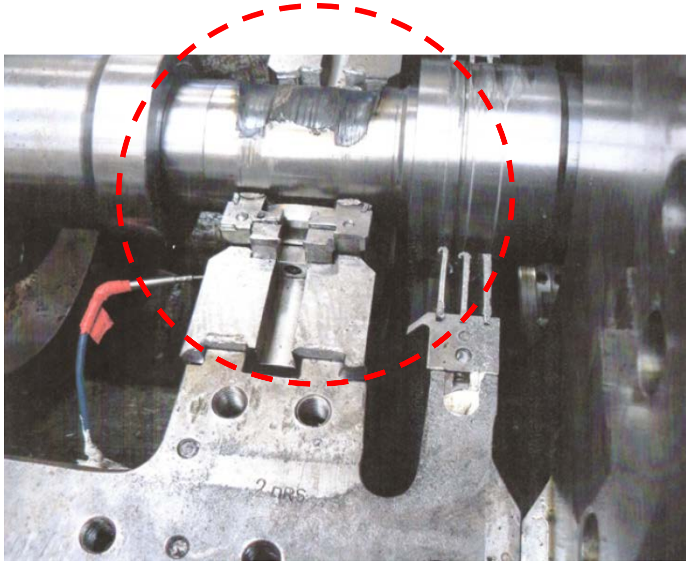
Presentation Outline

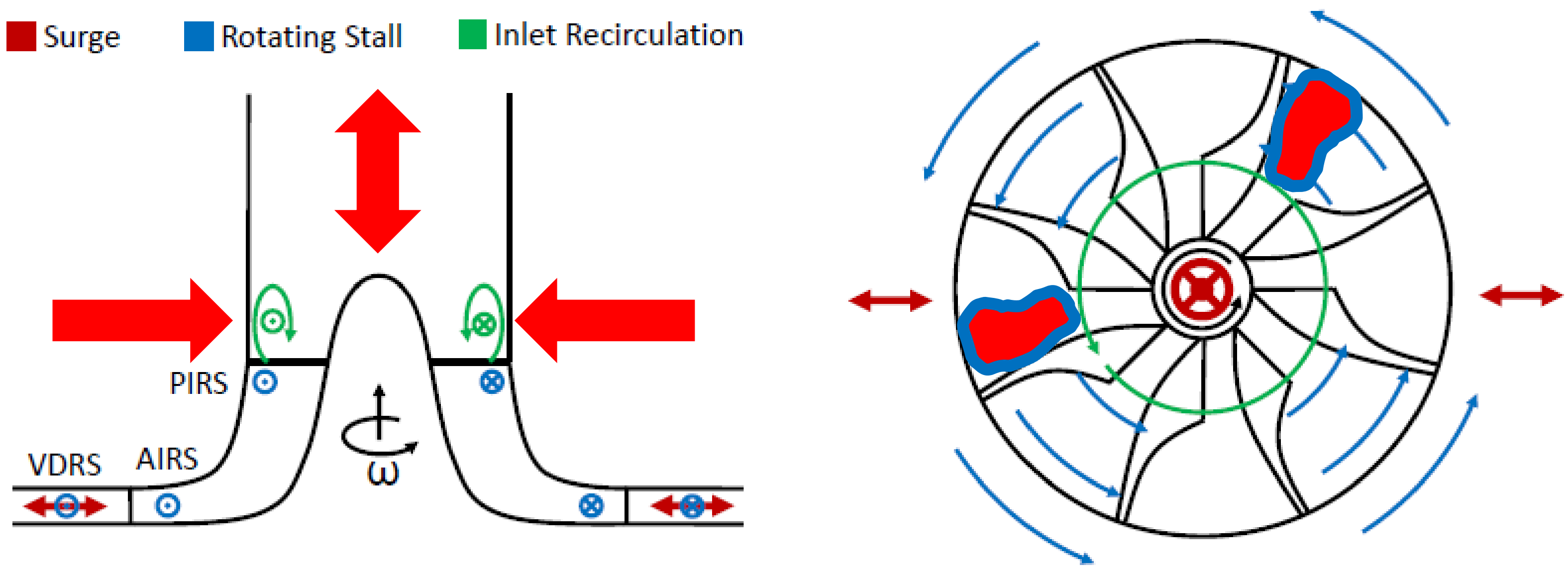
1. Centrifugal compressor working conditions
2. Test Stand
3. Feature Extraction/Classification
4. Artificial Intelligence
5. Discussion – towards explainable AI

Why it is important?

- **Centrifugal compressors are prone to aerodynamic instabilities;**
- **Appear at low mass flow-rate,**
- **Consequences:**
  - Light scenario – efficiency drop;
  - Severe scenario – immediate damage.
- **Things to consider:**
  - Theoretical conditions vs. condition monitoring,
  - Adaptability on different machines.



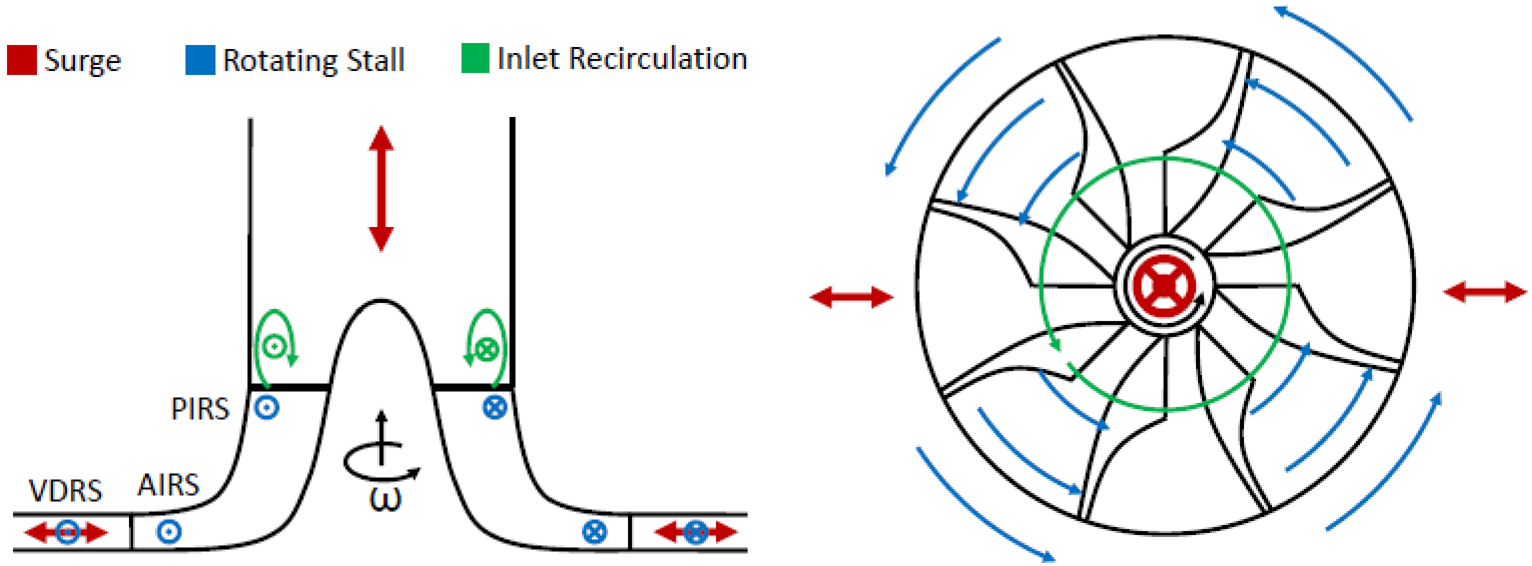
Instability classification



(a) cross-section

(b) top view

Instability classification



(a) cross-section

(b) top view

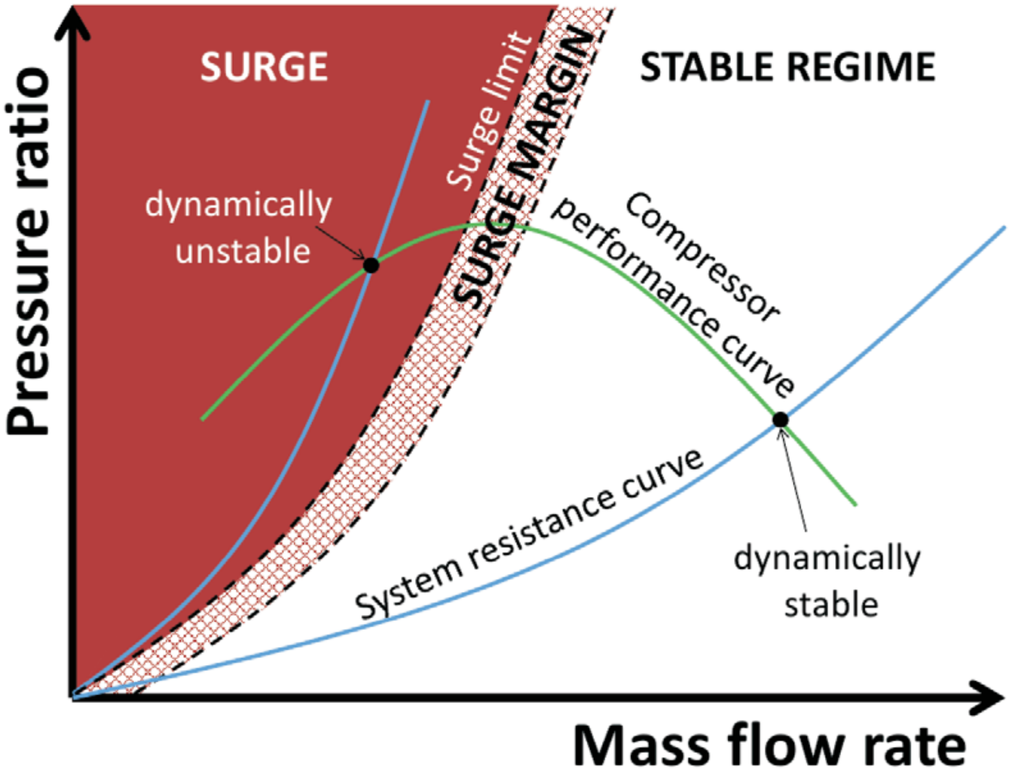
- **PIRS – progressive impeller rotating stall**
- **AIRS – abrupt impeller rotating stall**
- **VDRS – vaneless diffuser rotating stall**

⊗ **– flow moving from the observer**

⊙ **– flow moving towards the observer**

Classic protection

- **Only surge,**
- **Based on compressor map;**
- **Surge margin cuts efficiency by 10%-15%;**
- **No accounting for changing characteristic due to wear.**



Detection of instabilities

- **Dynamically sampled data from multiple sensors:**
  - thermal,
  - accoustic,
  - vibration,
  - pressure sensors.
- **Real-time data processing with complex algorithms.**

Detection of instabilities

- **Dynamicaly sampled data from multiple sensors**
  - thermal,
  - accoustic,
  - vibratio
  - pressur
- **Real-time**

Two main directions can be distinguished:

- **expert-knowledge based feature extraction,**
- **artificial intelligence methods.**

<u>Most important factors:</u>

- **pace of detection,**
- **robustness,**
- **universality across different compressors**

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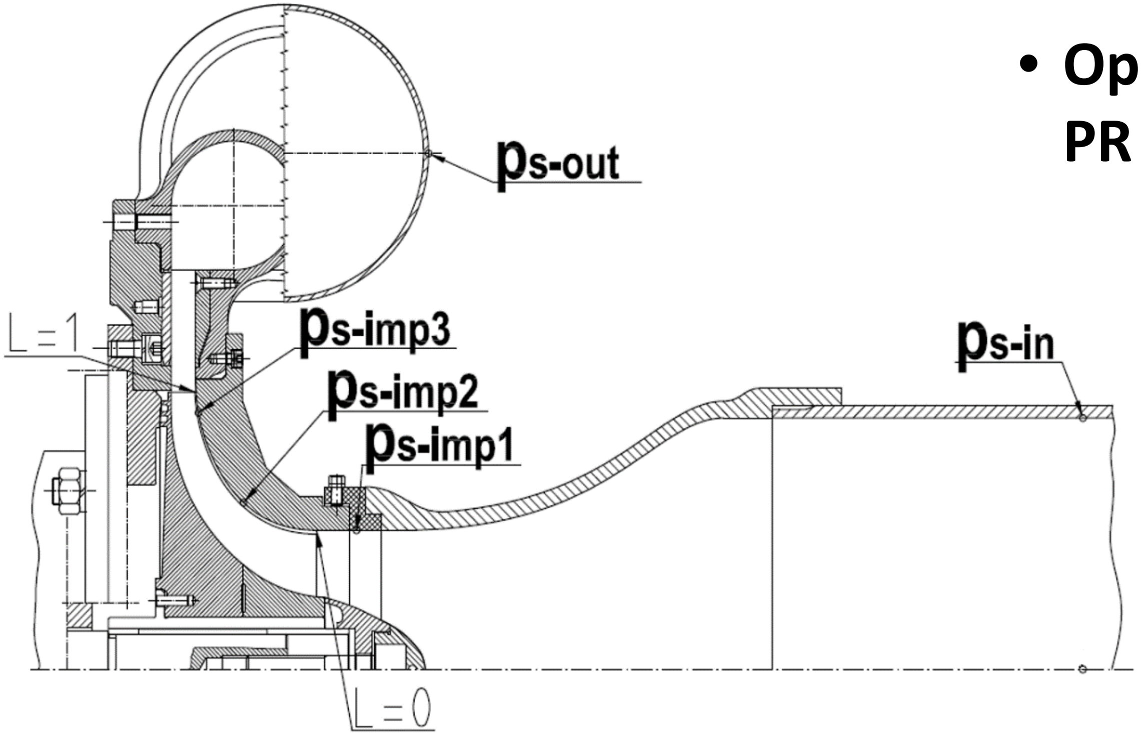
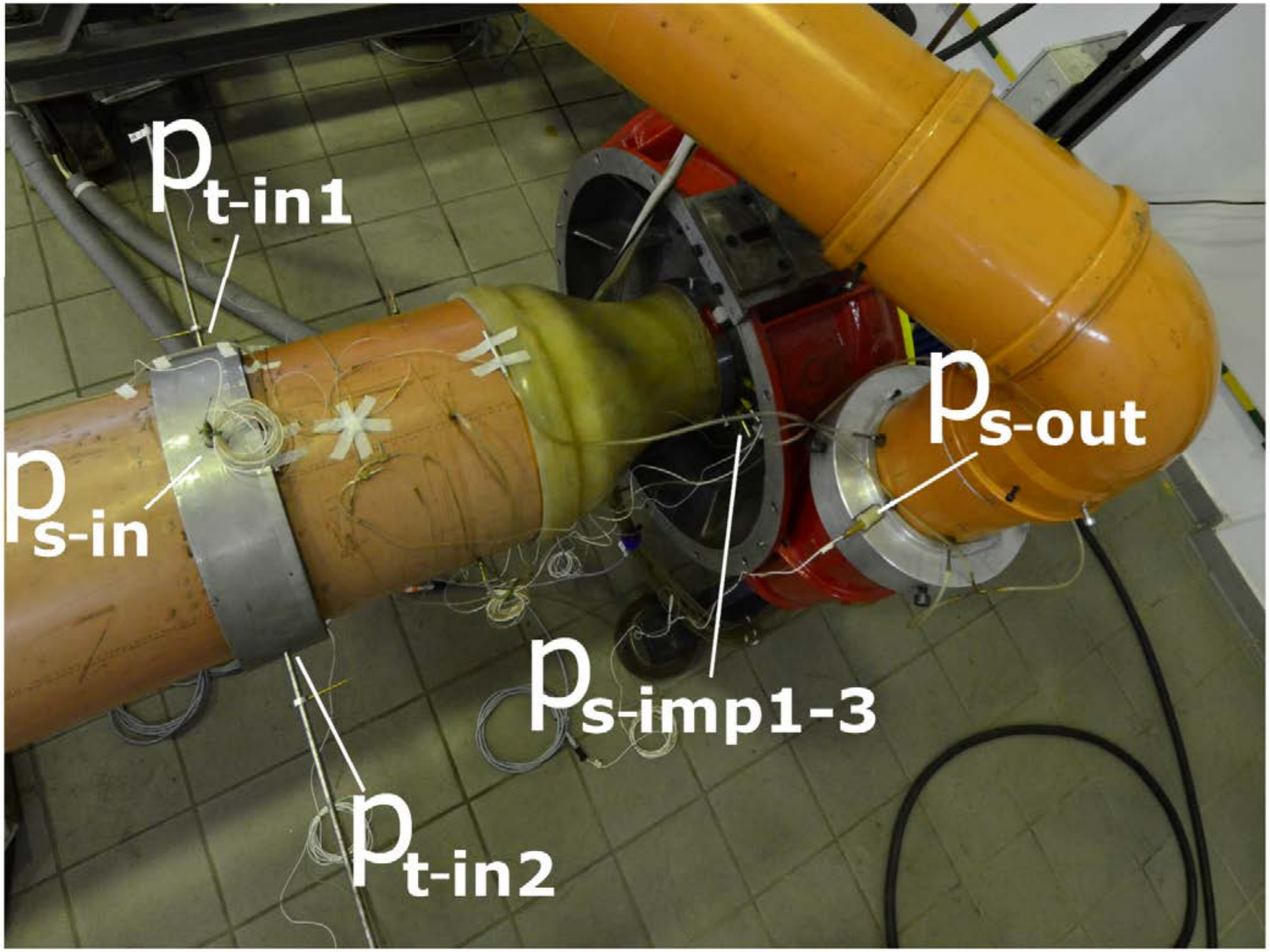
Test Stand

- **Impeller with 23 blades,**
- **Vaneless diffuser,**
- **Helmholz frequency ~11Hz.**



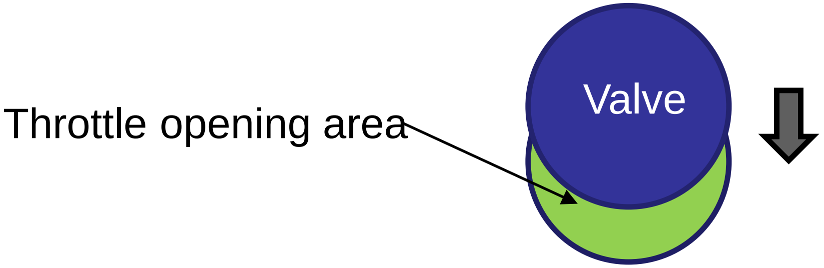
- **Design point:**
  PR 1.12/0.8 kg/s/120Hz
- **Operation:**
  PR 1.08/0.75kg/s/100Hz

Test Stand


$p_{t\text{-}in1}$
$p_{s\text{-}in}$
$p_{s\text{-}out}$
$p_{s\text{-}imp1\text{-}3}$
$p_{t\text{-}in2}$

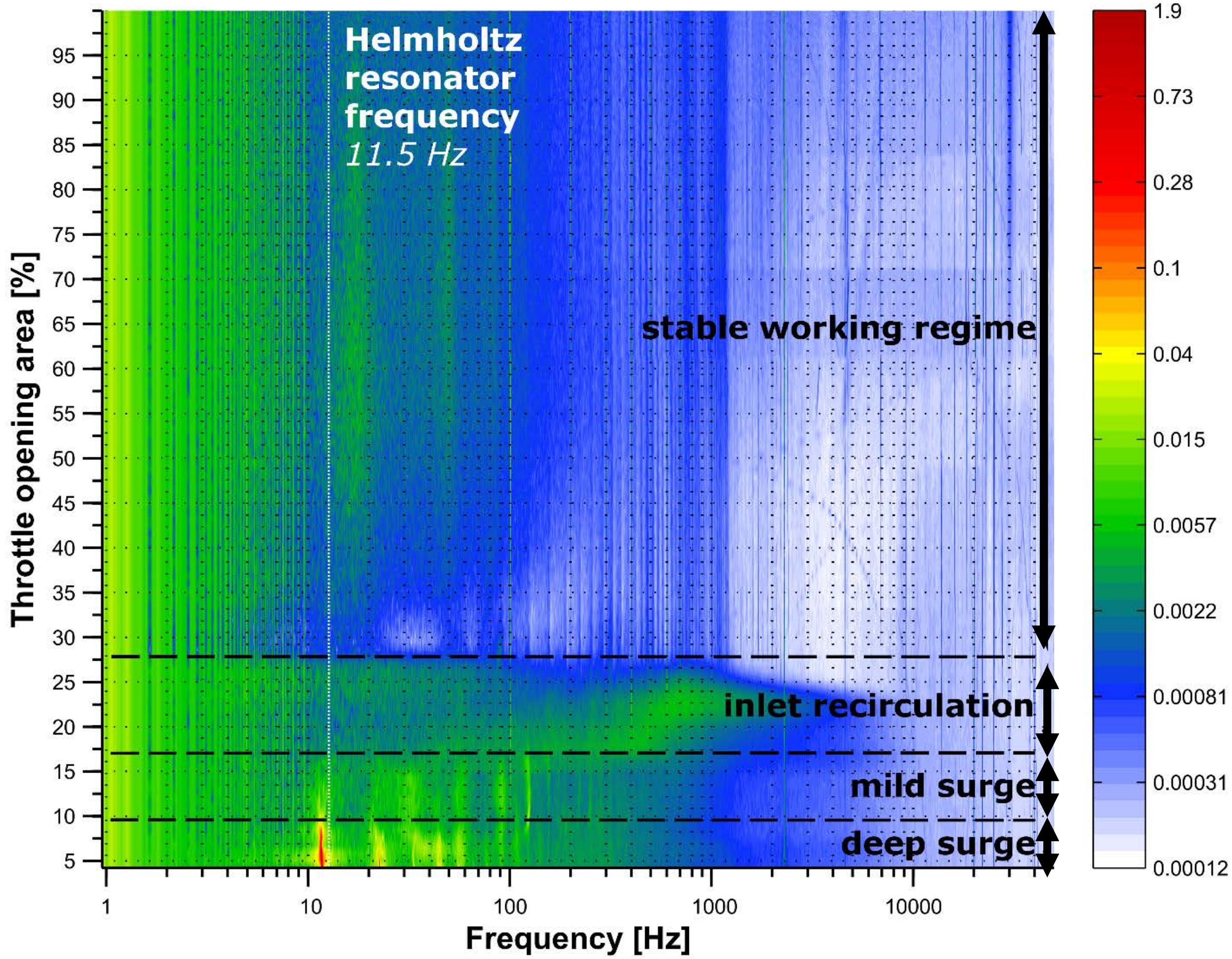
Data acquisition

- Quasi-dynamic analysis,
- Measurements at steady conditions for 20s @ 100kHz sampling rate;
- Resistance adjustment with valve at the outlet
- Throttle Opening Area (TOA) [%];
- Measurements from 100% to 5% of TOA with 1% increment.



Machine working conditions

Pressure at the blower inlet [kPa]



TOA [%]	Flow conditions
5-11	Deep surge
12-18	Mild surge
19-25	Inlet recirculation
26 - 33	Stable

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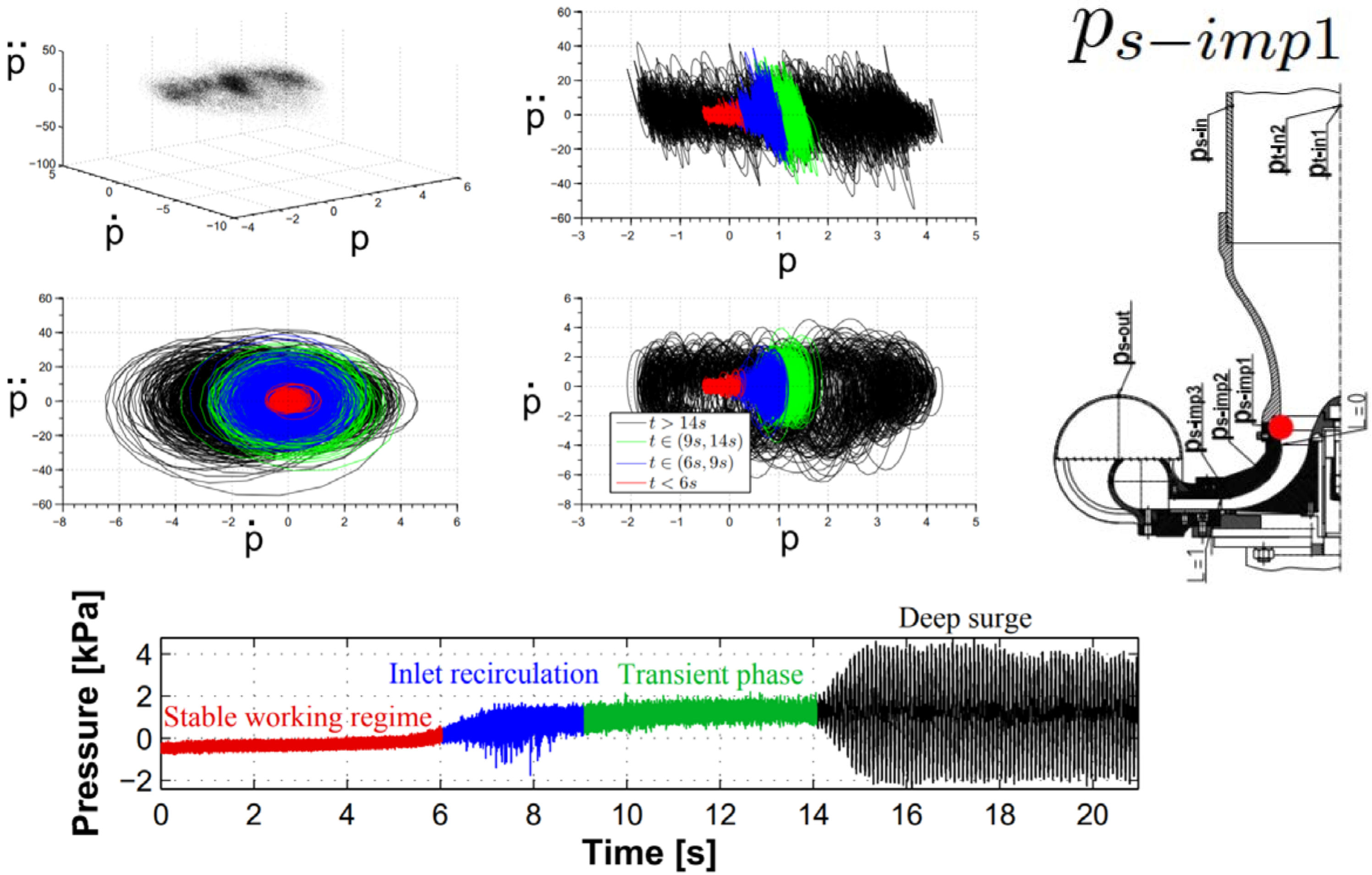
Feature extraction

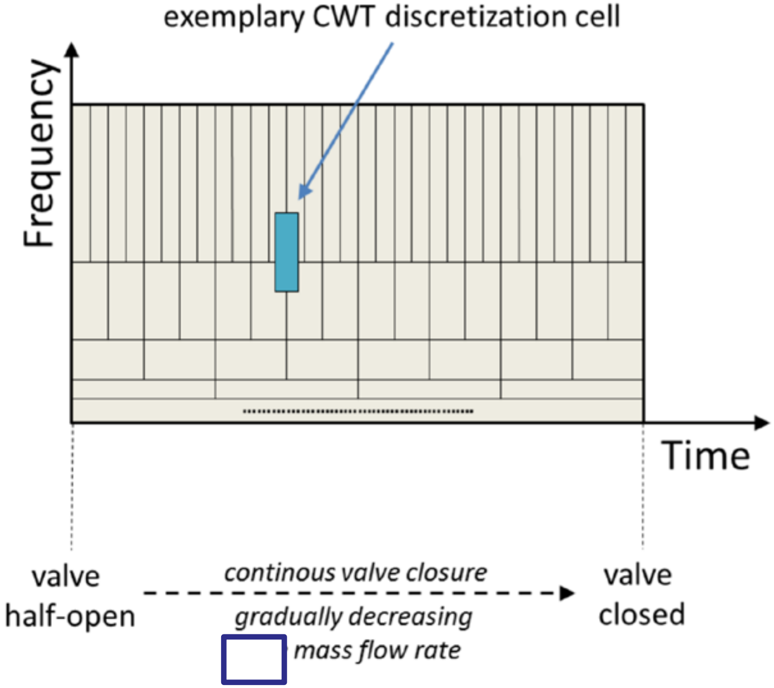
- **Dividing a signal into a number of components;**
- **Indicates presence of features burried in the signal;**
- **Often includes frequency, time or joint time-frequency analysis.**
- **Exemplary feature extraction methods are:**
  - Phase portrait – feaures extracted from PP’s;
  - Continous Wavelet Transform – Changes in frequency spectra;
  - Singular Spectrum Analysis – obtaining eignvalues of a matrix;
  - Empirical Mode Decomposition – extract modes based on envelopes of the signal.

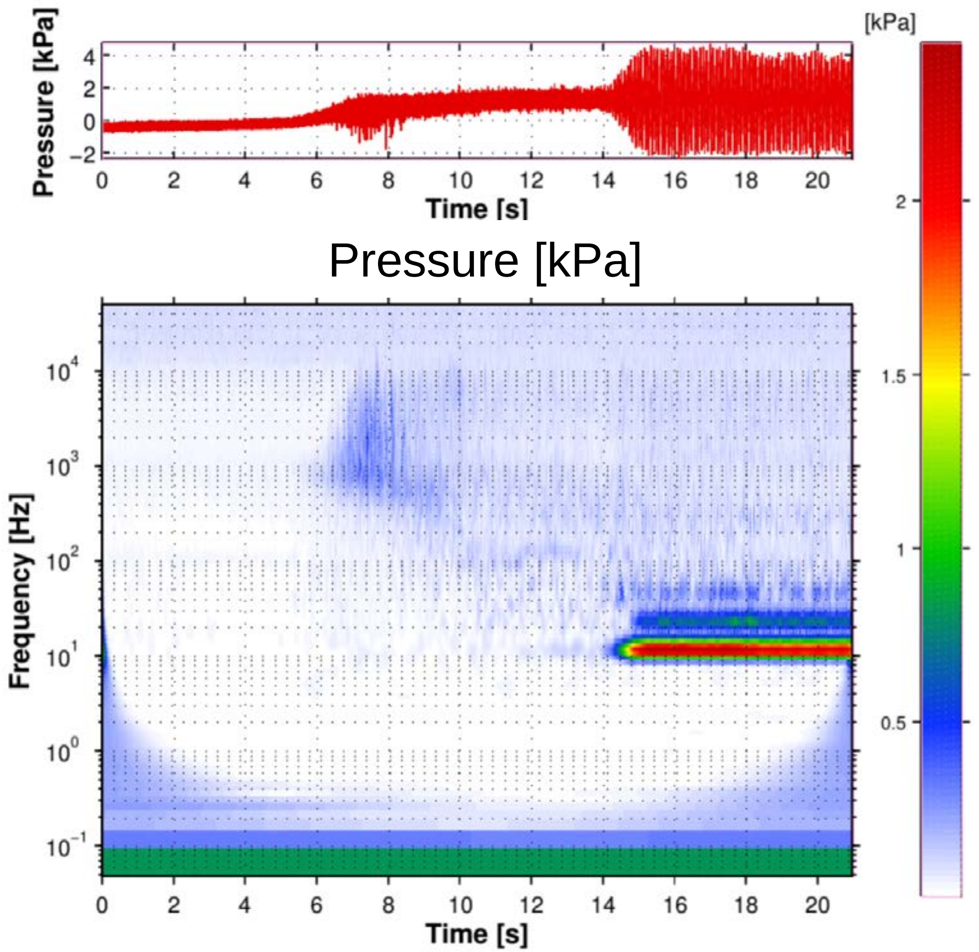
Phase Portrait Tracking



Liśkiewicz, G. (2020). Efficient and reliable surge prevention algorithm for centrifugal compressor. *Aircraft Engineering and Aerospace Technology*
Liskiewicz, G., Kabalyk, K., Jaeschke, A., Grapow, F., Kulak, M., Kryłłowicz, W., ... & Shen, X. (2021). Experimental Analysis of Surge-Detection System Based on Pressure Derivatives at Part-Speed Operation. *Journal of Engineering for Gas Turbines and Power*, *143*(5), 051018..

Continous Wavelet Transform (CWT)





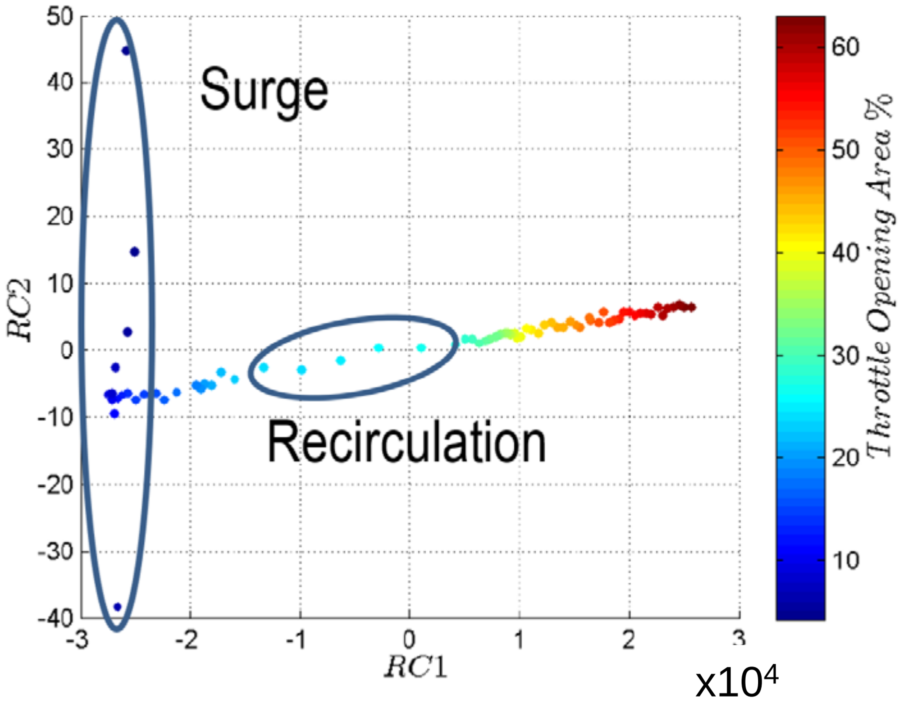
Liskiewicz, G., & Horodko, L. (2015). Time-frequency analysis of the surge onset in the centrifugal blower. *Open Engineering*, *5*(1).

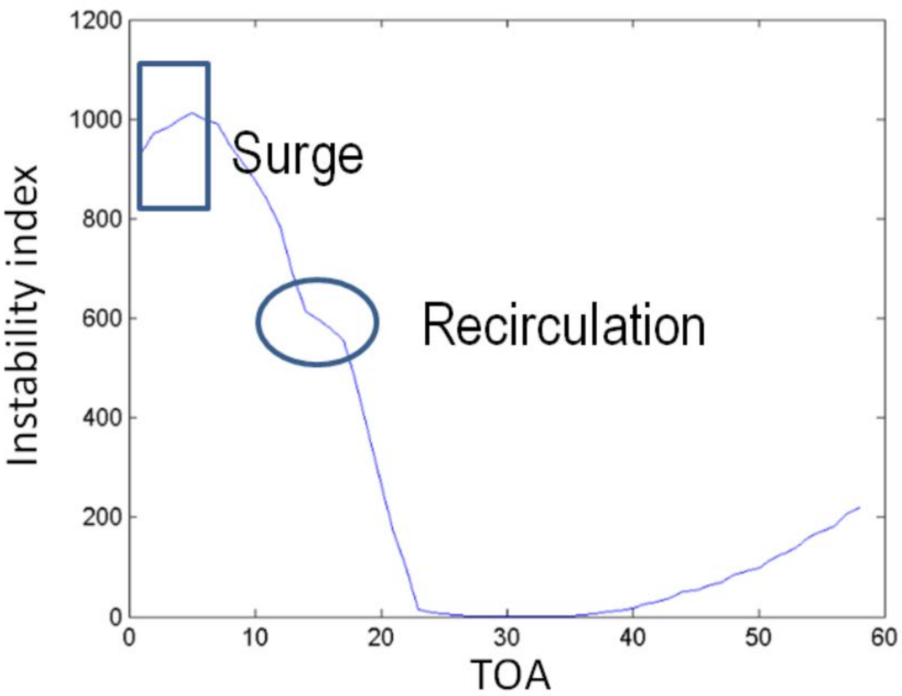
Singular Spectrum Analysis

Clustering of unstable flow structures,

Projection on Reconstructed Components (RC)

Mahalanobis distance

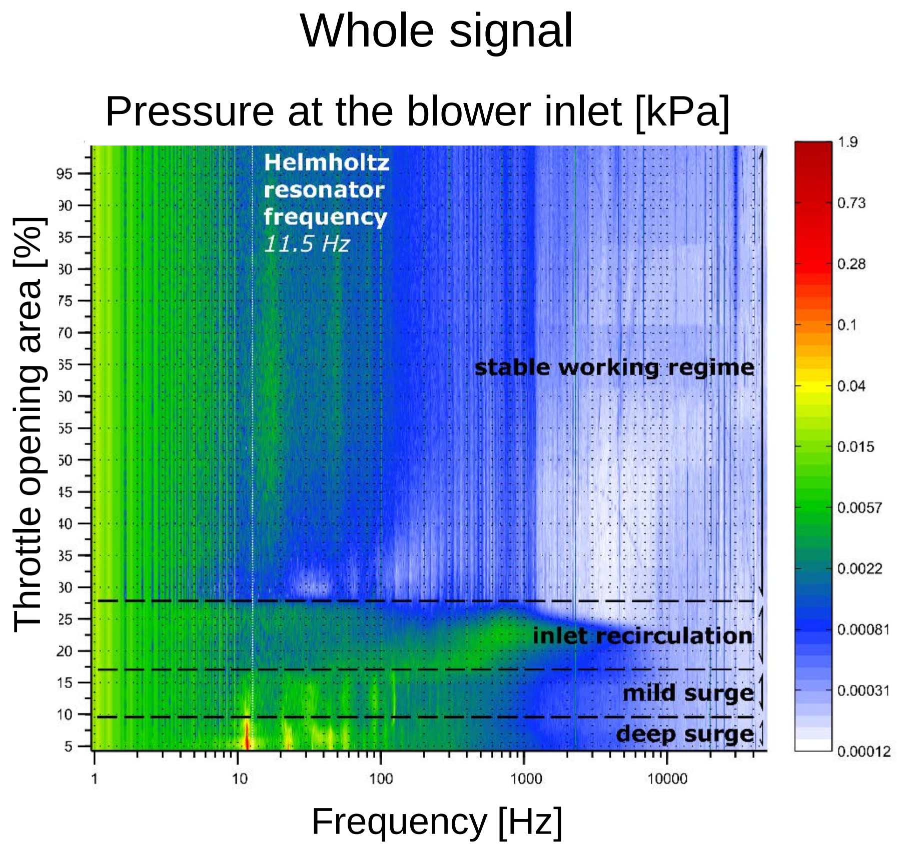


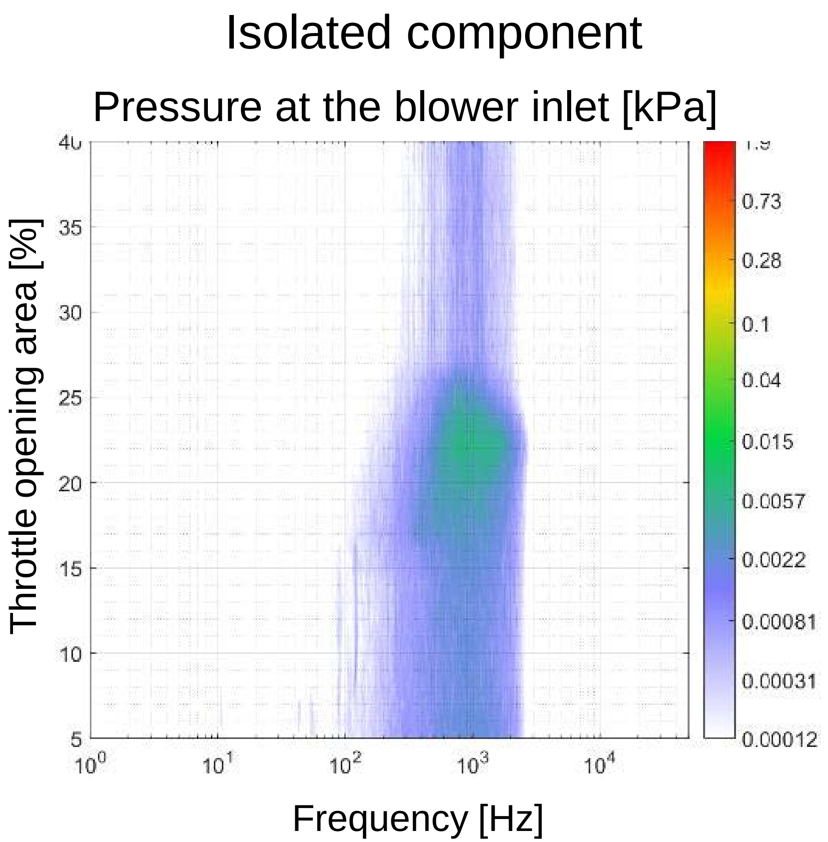


Garcia, D., & Liśkiewicz, G. (2016). Stable or not stable? Recognizing surge based on the pressure signal. *Transactions of the Institute of Fluid-Flow Machinery*.

Singular Spectrum Analysis

Isolation of Inlet Recirculation in single component



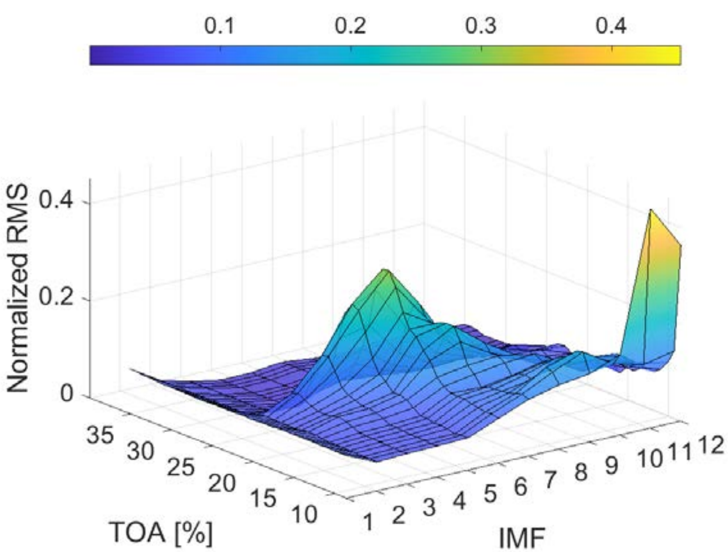


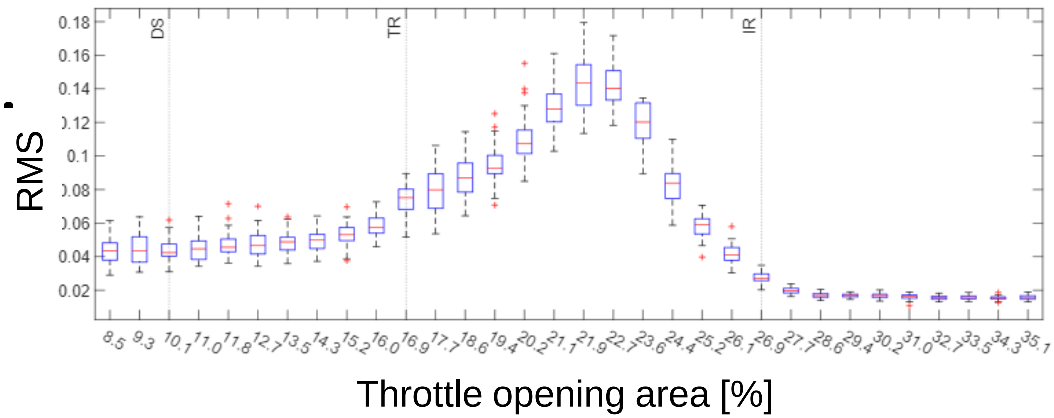
Logan, A., Cava, D. G., & Liśkiewicz, G. (2021). Singular spectrum analysis as a tool for early detection of centrifugal compressor flow instability. *Measurement*, *173*, 108536.

Empirical Mode Decomposition

Identification by:

- **Value of components,**
- **Variation of components.**





RMS

Throttle opening area [%]

Good feature extraction

- The features extracted from signal are either not fully universal, not robust enough, their extraction takes too long or they need long input signal to ensure detection;
- The efforts of many scientists and engineers focus on finding better ways of detecting aerodynamic instabilities;
- The research on feature extraction methods could use guidance about possible directions of development.

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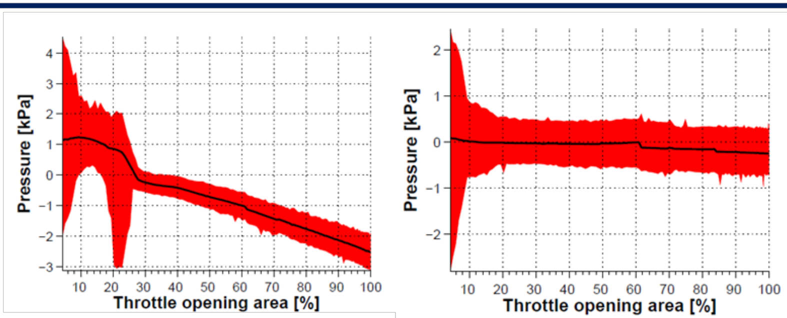
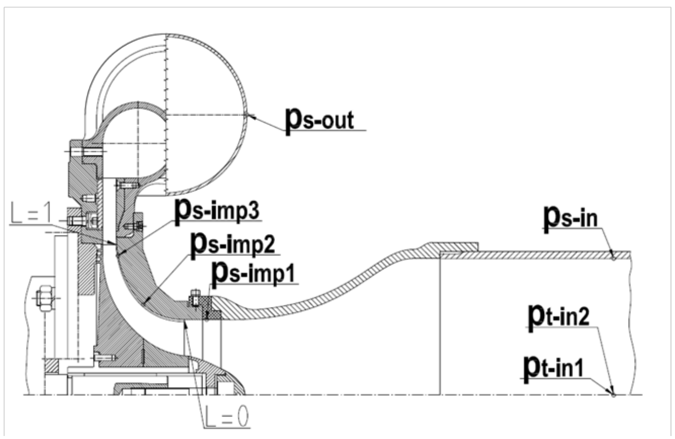
Training

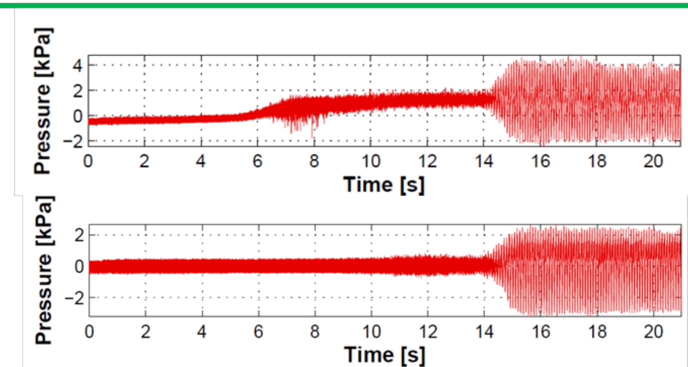


TOA	Stability	Gauges	Name
$TOA > 27\%$	stable	all	nominal work
$TOA \in (17\%, 27\%)$	transient	p_{s-imp1}, p_{s-imp2}	inlet recirculation
$TOA \in (10\%, 17\%)$	unstable	all	transient phase
$t < 10\%$	unstable	all	deep surge

Quasi-dynamic measurements



Validation



Time range	Stability	Gauges	Name
$t < 6$ s	stable	all	nominal work
$t \in (6\text{ s}, 9\text{ s})$	transient	p_{s-imp1}	inlet recirculation
$t \in (9\text{ s}, 14\text{ s})$	unstable	all	transient phase
$t > 14$ s	unstable	all	deep surge

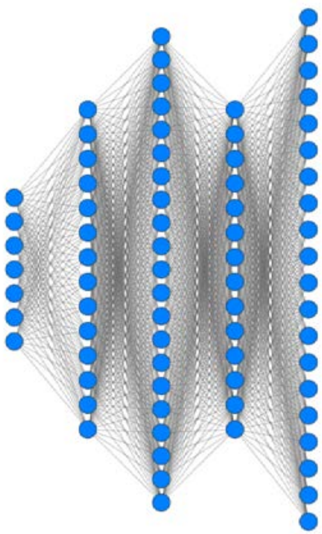
Dynamic measurements

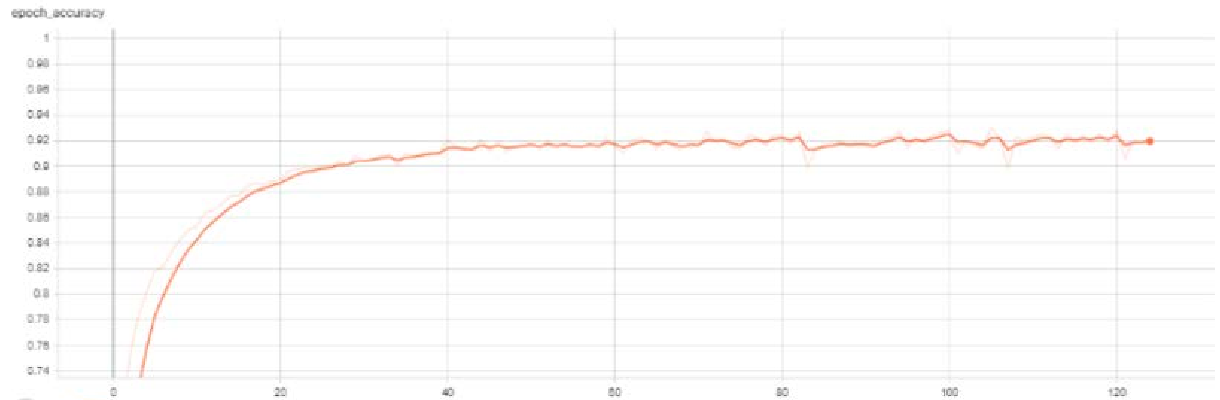
Classification quality to confirm the classifier functionality

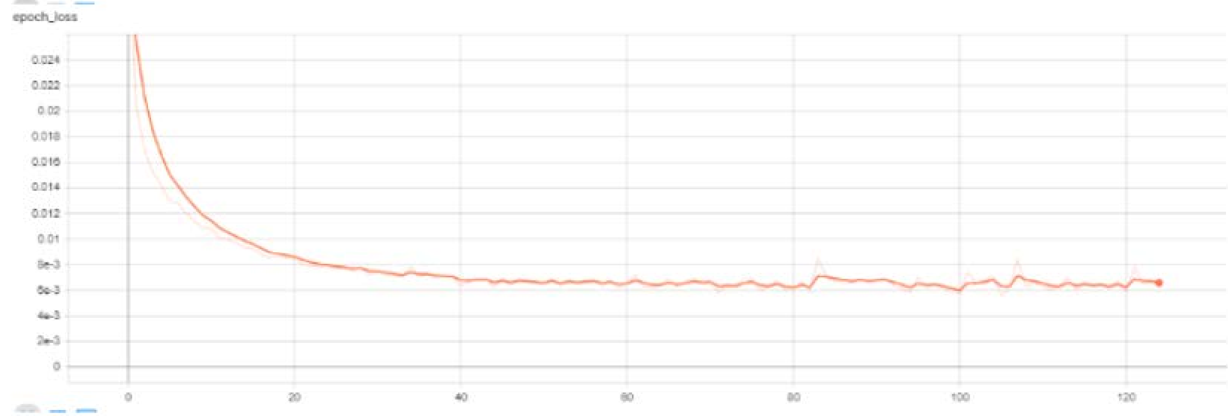
Understanding of the features through correlation with standard and data driven indicators

Classic Artificial Intelligence

- **Preliminary studies show that with simple fully-connected neural networks, an accuracy of over 90% can be achieved.**







Classic Artificial Intelligence

- **Single transducer**

Transducer number	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Number of data points *[*10³]*	80	80	80	80	80	80	80
Outcomes *[%]*	64	16	32	40	63	20	15
Good/bad prediction	25/55	71/9	53/27	57/23	37/43	57/23	70/10

- **Two transducers**

Transducers pair	**1-5**	**1-4**	**4-5**
Number of data points *[*10³]*	80	80	80
Outcomes *[%]*	89	86	71
Good/bad prediction	5/75	15/65	30/50

- **Three transducers**

Transducers triple	**1-5-6**	**1-5-6**	**1-4-5**	**1-4-5**
Number of data points *[*10³]*	80	80	80	80
Outcomes *[%]*	93	92	90	90
Good/bad prediction	6/74	5/75	11/69	5/75

Artificial Intelligence - challenges

- **Overfitting/bad data;**
- **No supervision over causality;**
- **Not enough training data;**
- **…**

**This means, that in not fully examined scenarios,
AI cannot be fully trusted.**

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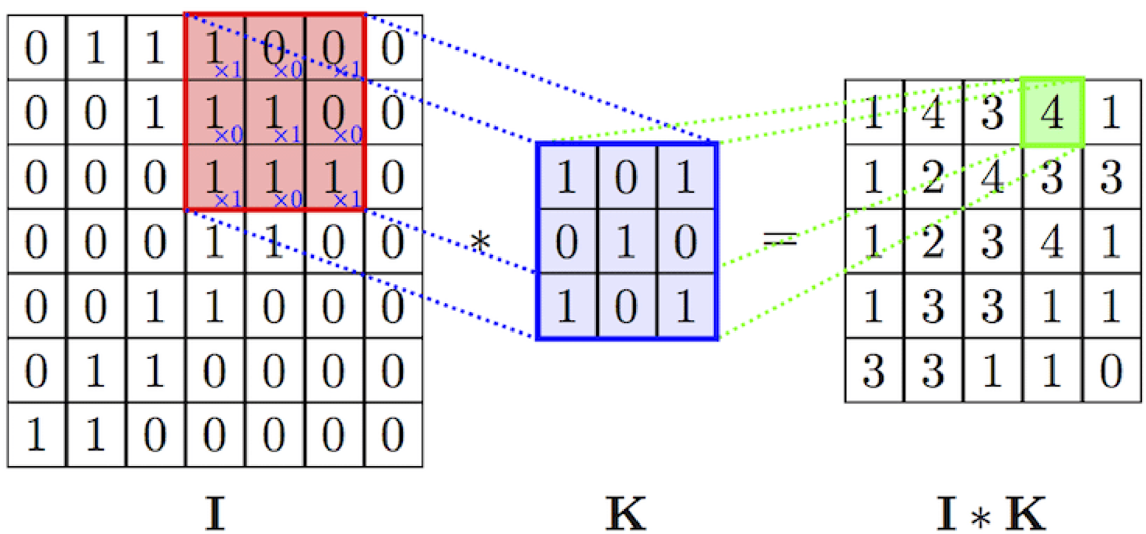
Towards explainable AI

- **Explainable AI – need to understand how machines *think;***
- **Especially ML – black-box models are as well understood as they are tested;**
- **Many approaches – examination of existing models, knowledge fine-tuning, knowledge retrieval under constraints, hybrid models – sequential, parallel, interactive;**
- **Why? Less data, better understanding, new knowledge!**

Research approach

- **Dynamic feature extraction with information diffusion control;**
- **Convolutiona Neural Networks (CNN) with introduced patterns.**

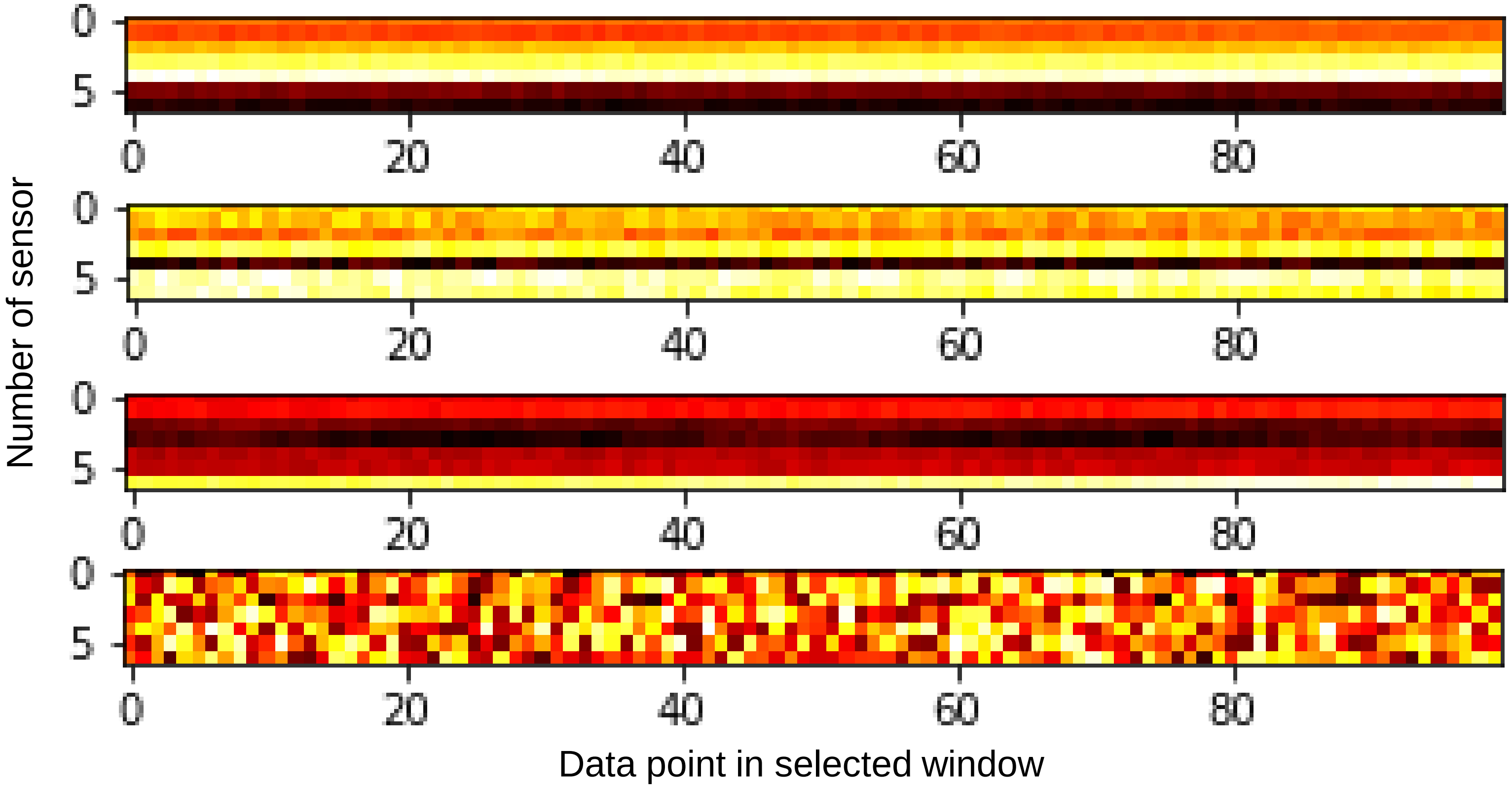


Research approach

- **Pressure signal is normalized to obtain a generalized case;**
- **It can be visually represented through a series of pixels having a color representative for the pressure value;**
- **A window of observations is chosen to make the network learn time-dependent features.**

Research approach

- **Diffusion control,**
- **Observable/learned features.**



Advantages

- New, less obvious features;
- Better transfer to new scenarios;
- Less training data;
- Important knowledge extraction to simpler models.

Further steps

- Build knowledge base;
- Connect extracted features into more complex concepts;
- Extract new features?
- Zero-shot prediction?

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Thank You!

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