Data Analytics for CERN Control Systems

CERN Machine Learning openlab workshop

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CERN: one of the world's largest automation systems

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(Automation) Infrastructure

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Experiments

50 times more data than today
in the next 10 years!

components

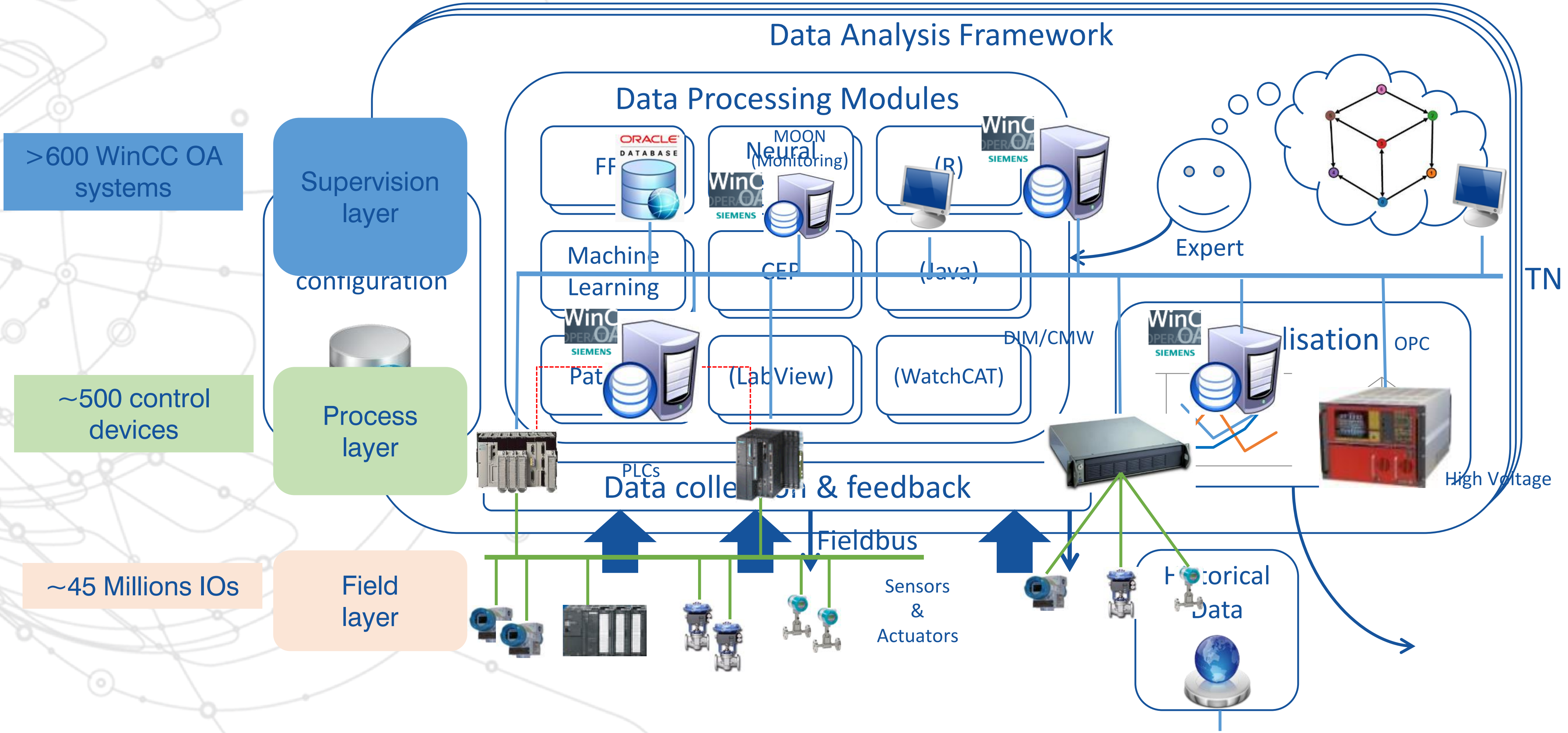
› massive amount of operational data generated every day

mode)

› over 1 PB/s of data generated by the detectors
› Up to 50PB/Year of stored data

Our vision of the analytics framework

Scalable and fault-tolerant !!!



CERN control system use-cases

Based on real examples

Use-cases classification

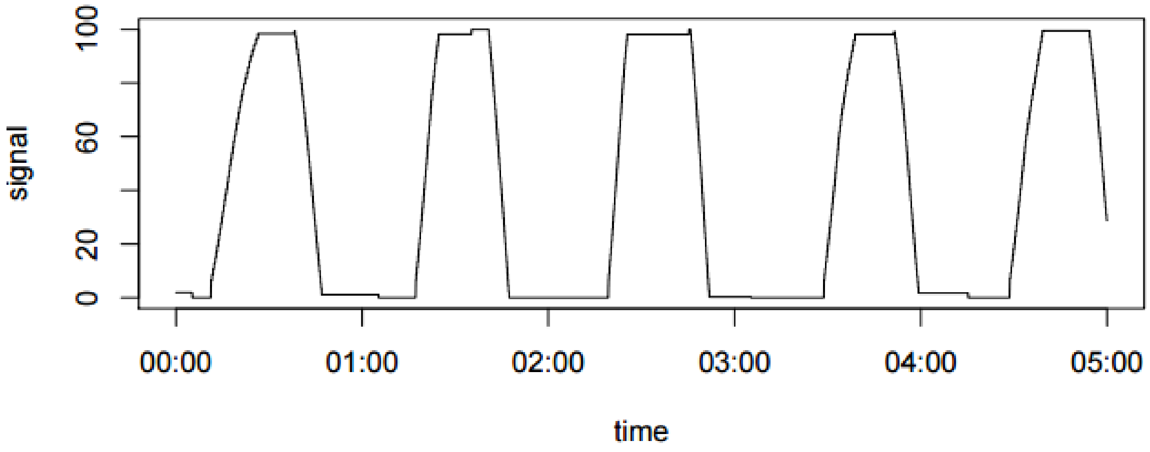
- **Online monitoring**
  - Continuous service to analyse the system status and inform operators in case of fault detection
- **Fault diagnosis**
  - "Forensics" analysis of system faults that have already happened in the past. In some cases root-cause analysis
- **Engineering design**
  - Analysis of historical data to draw conclusions about system behaviours which could be helpful to improve / optimize the system under analysis

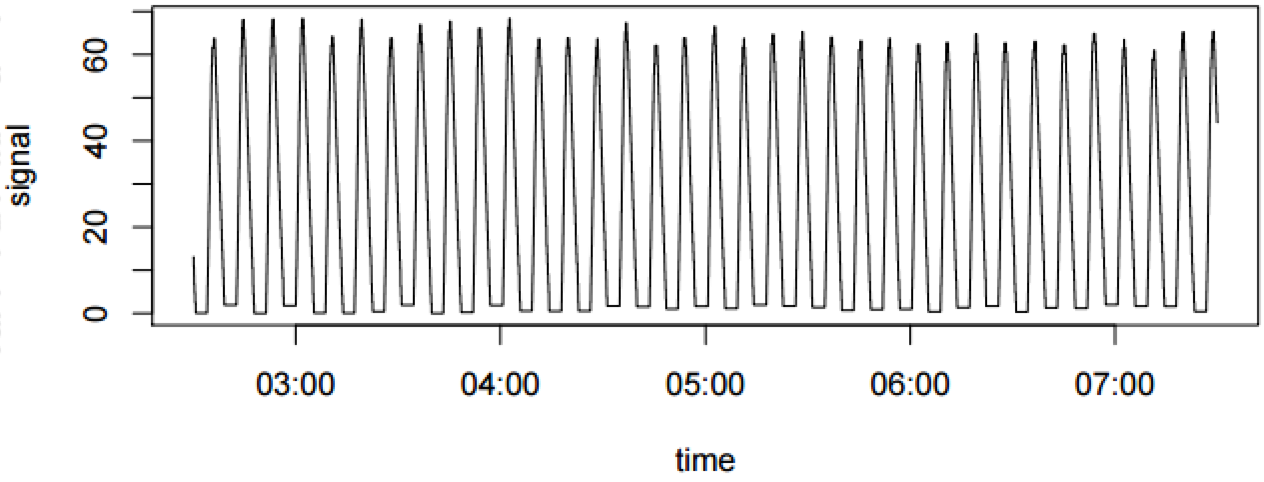
Online monitoring

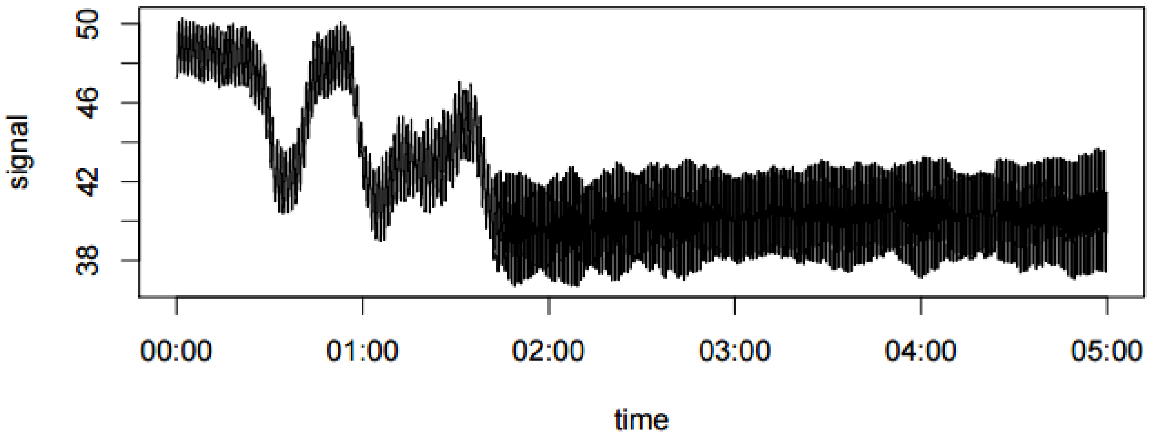
- Oscillation analysis in cryogenics valves (CRYO, CV)
- Online analysis of control alarms

Oscillation analysis for cryogenics valves

- **Goal: detect whenever a signal is oscillating in any anomalous way. Impact on:**
  - Control system stability
  - Increased communication load
  - Maintenance (use of actuators)
  - Safety
  - Performances (Physic time)







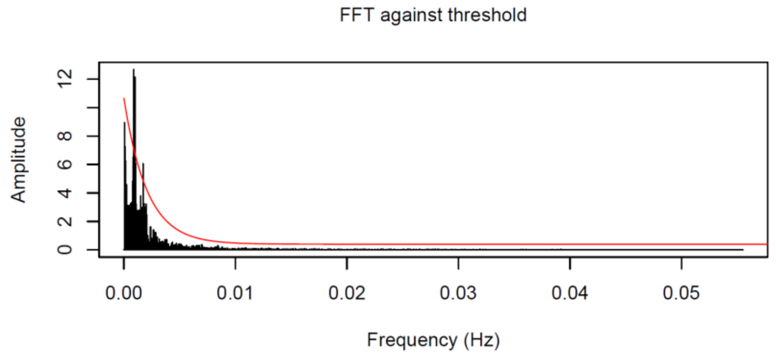
Oscillation analysis flow

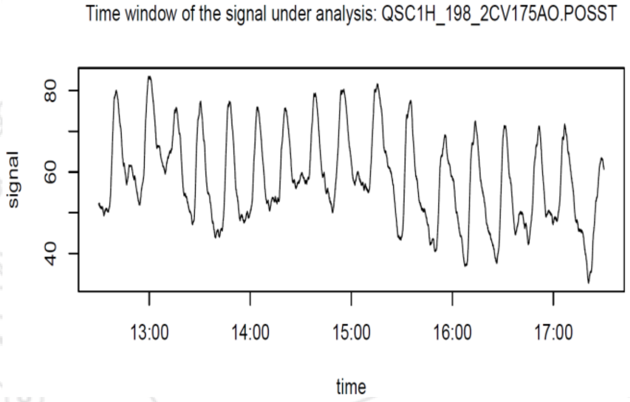
Use of machine learning:

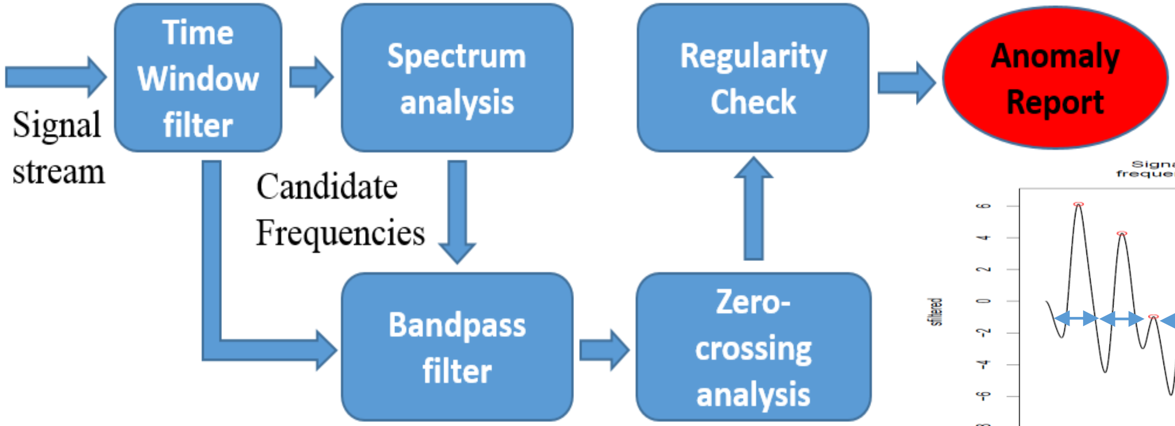
- Threshold learning model
- Dynamic learning
- Associate the oscillation with system status conditions

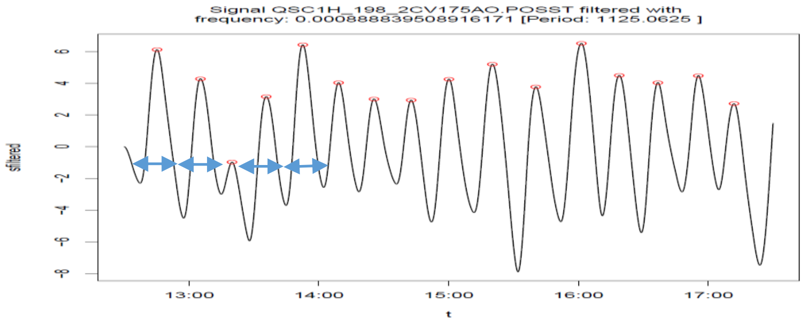
On-line analysis:

- > 3000 sensors
- Continuous analysis

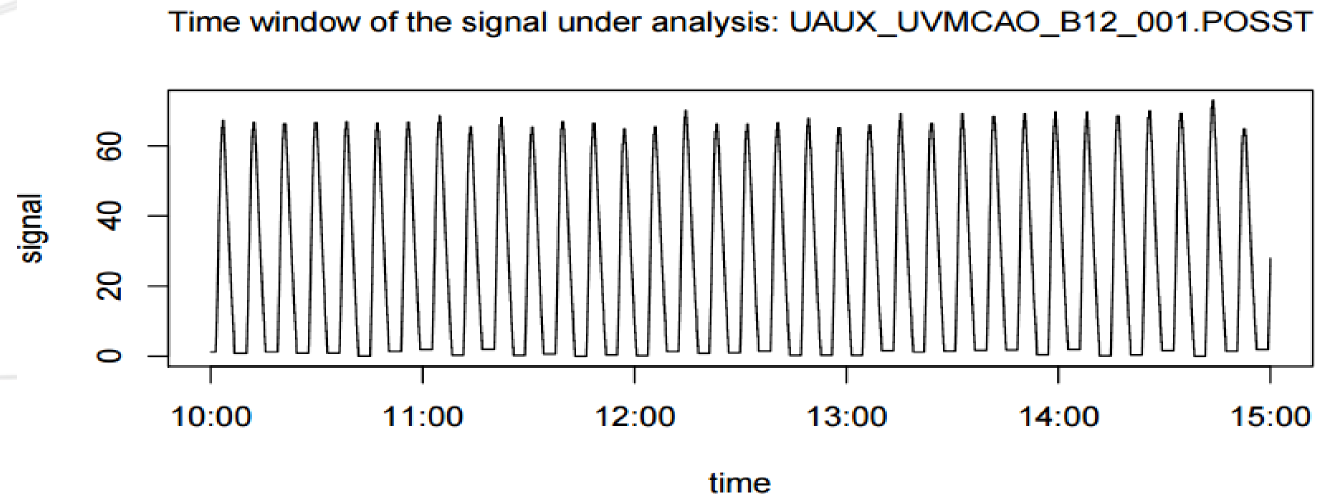


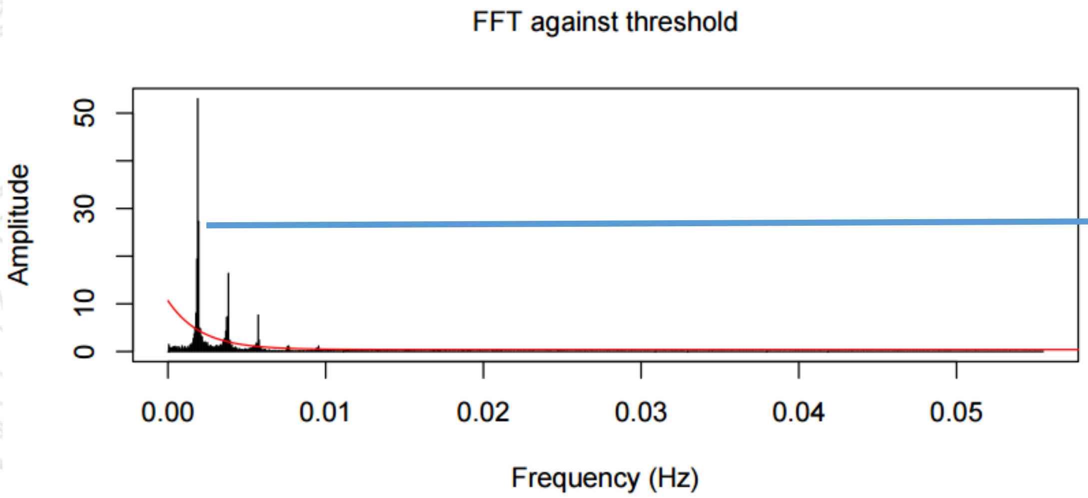


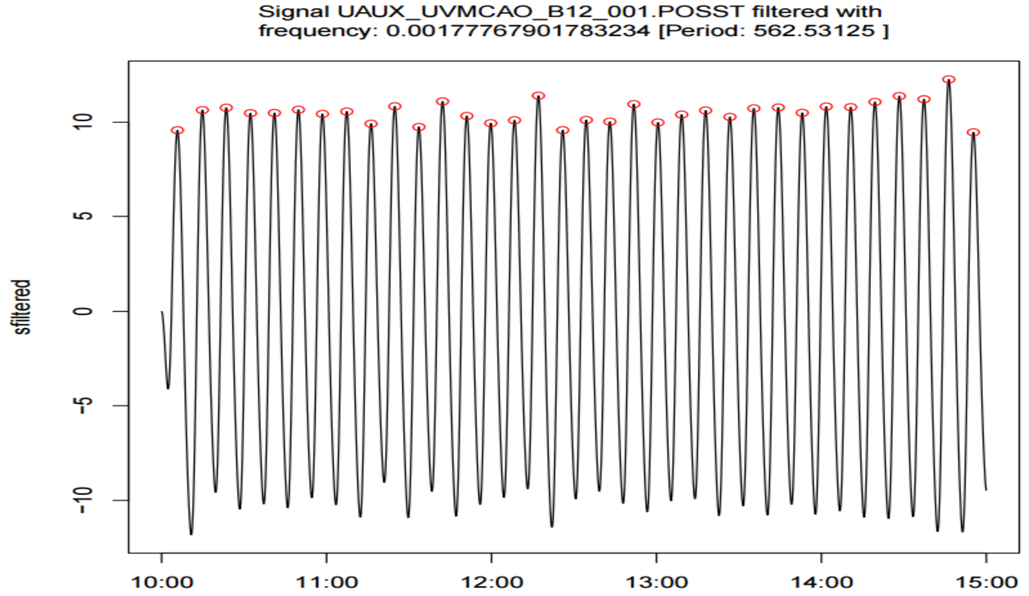




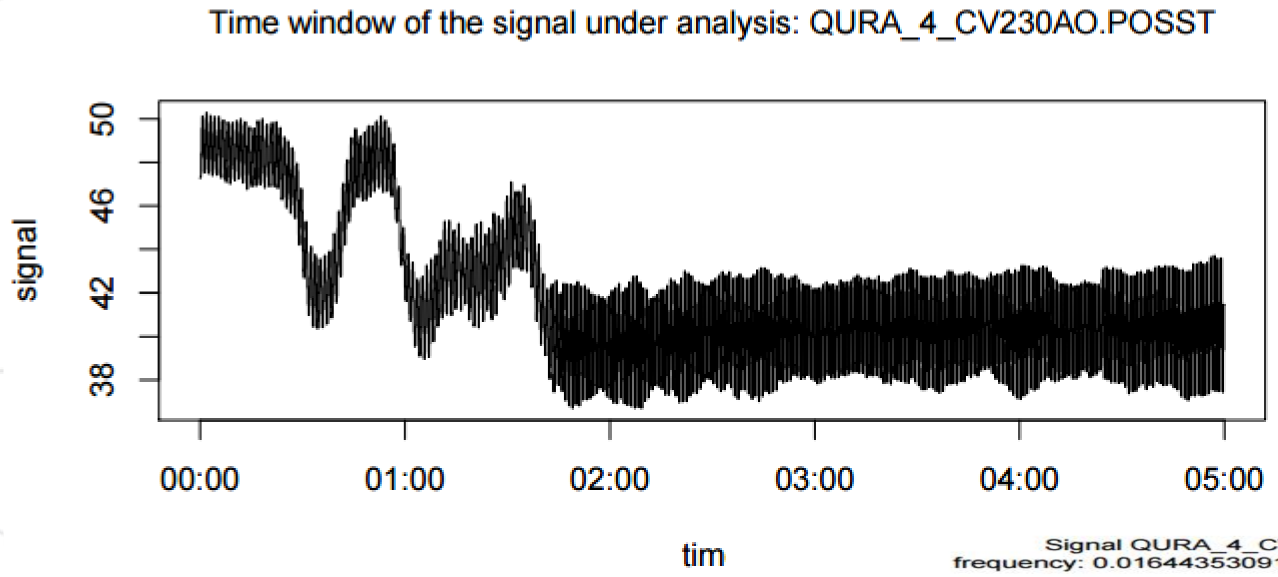
Oscillation detection Ex#1

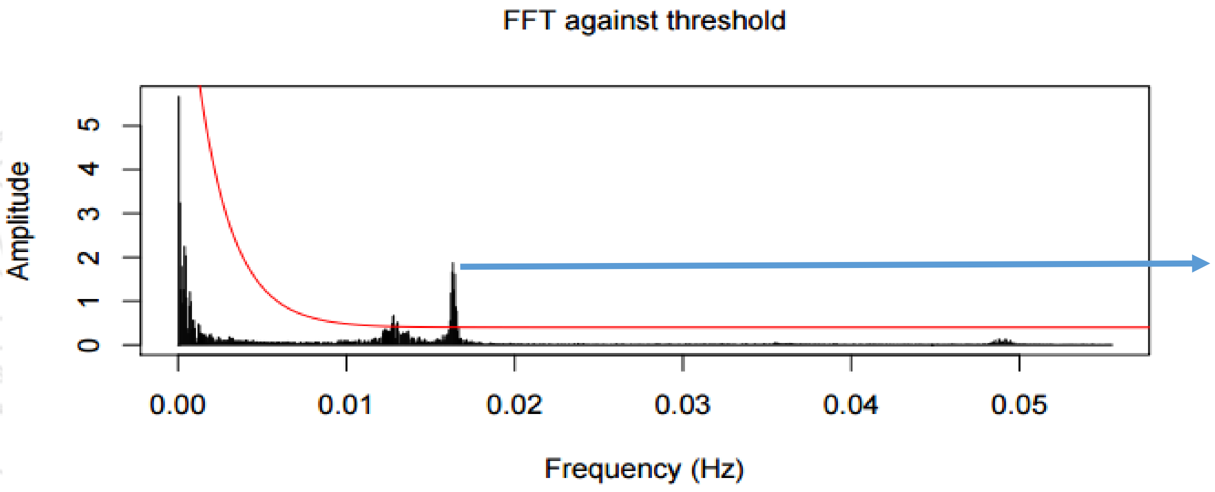


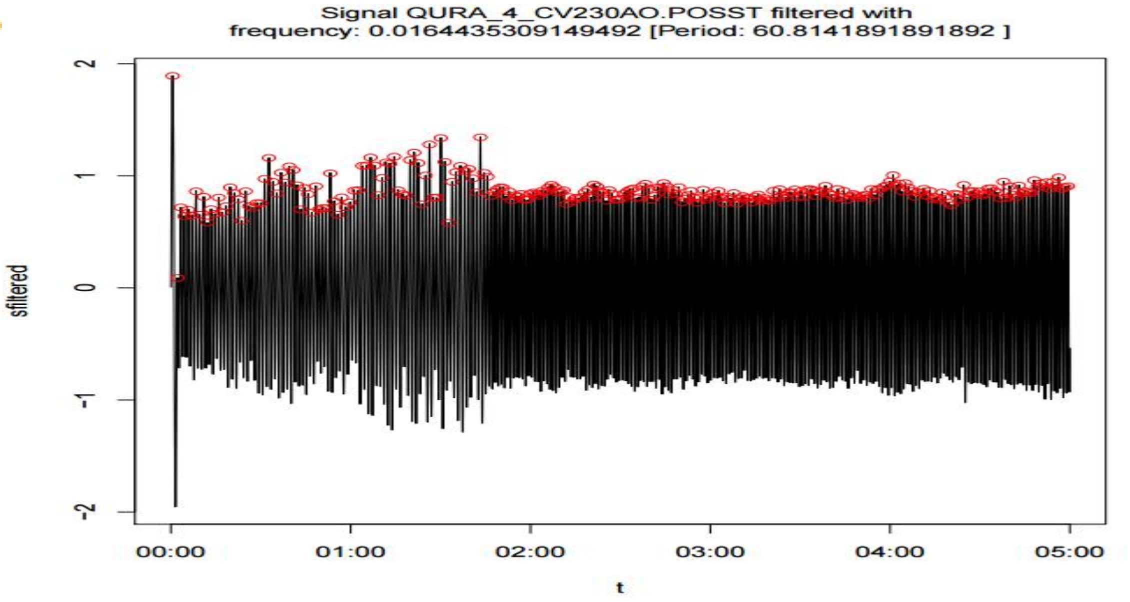




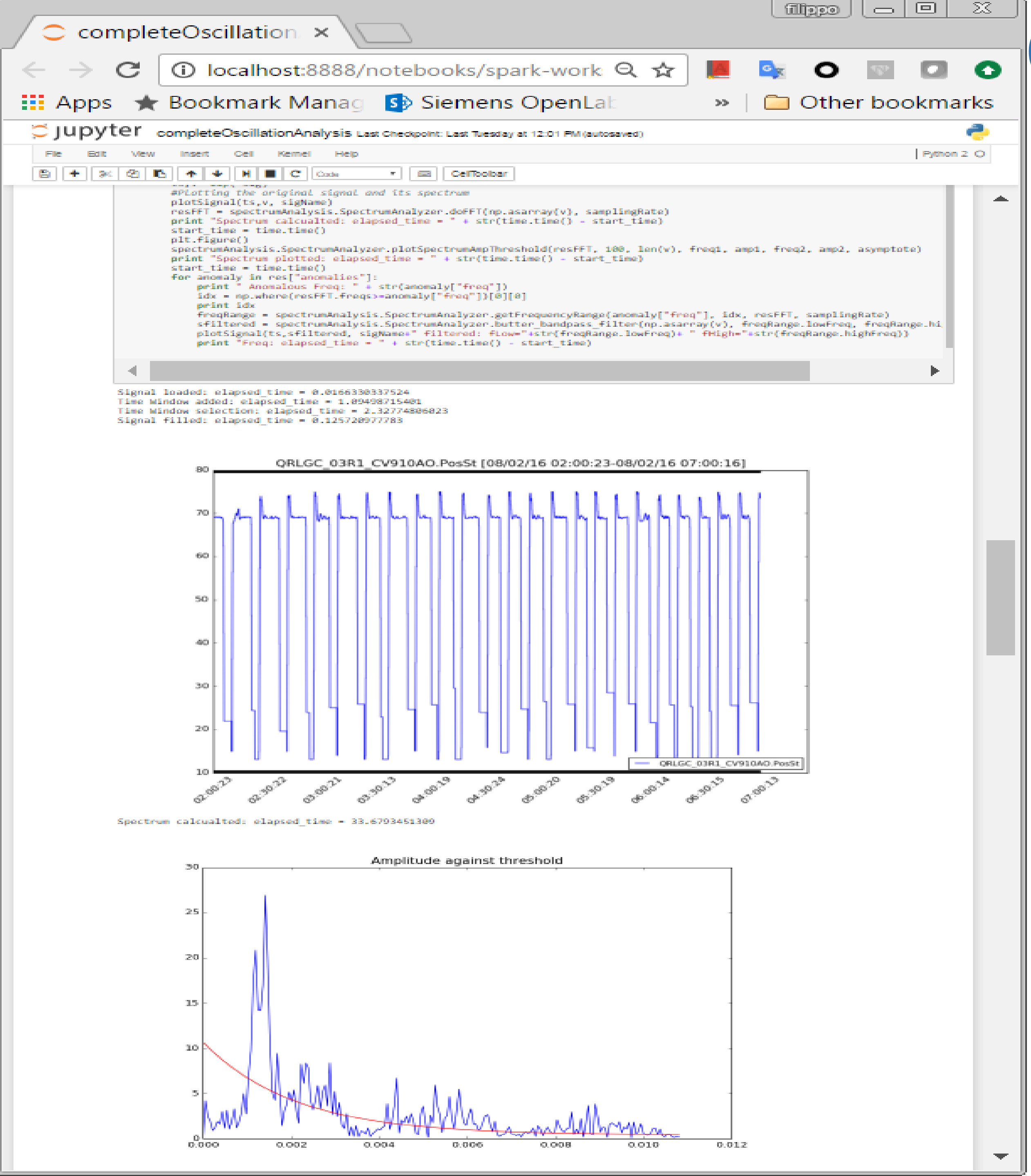
Oscillation detection Ex#2

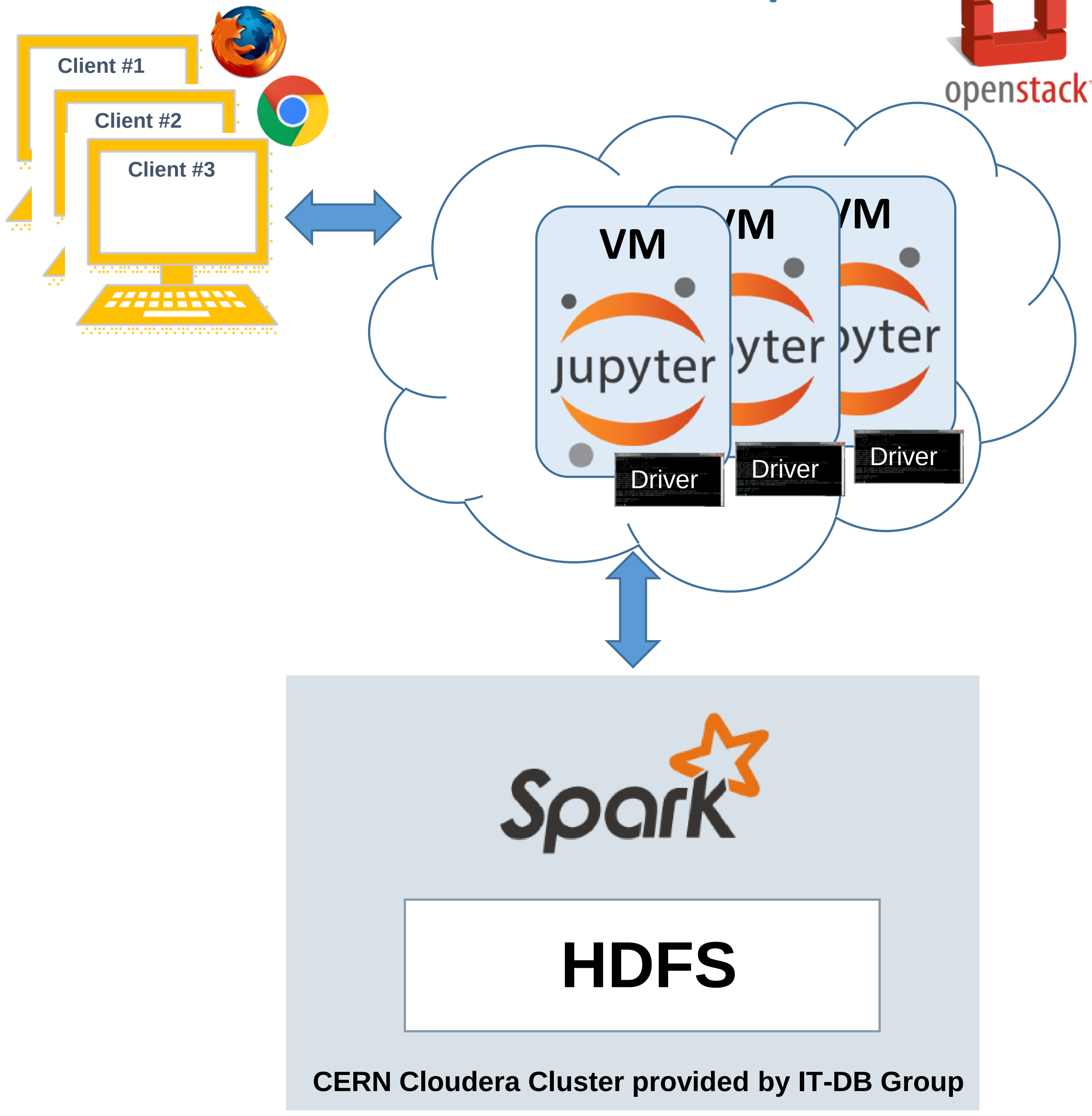






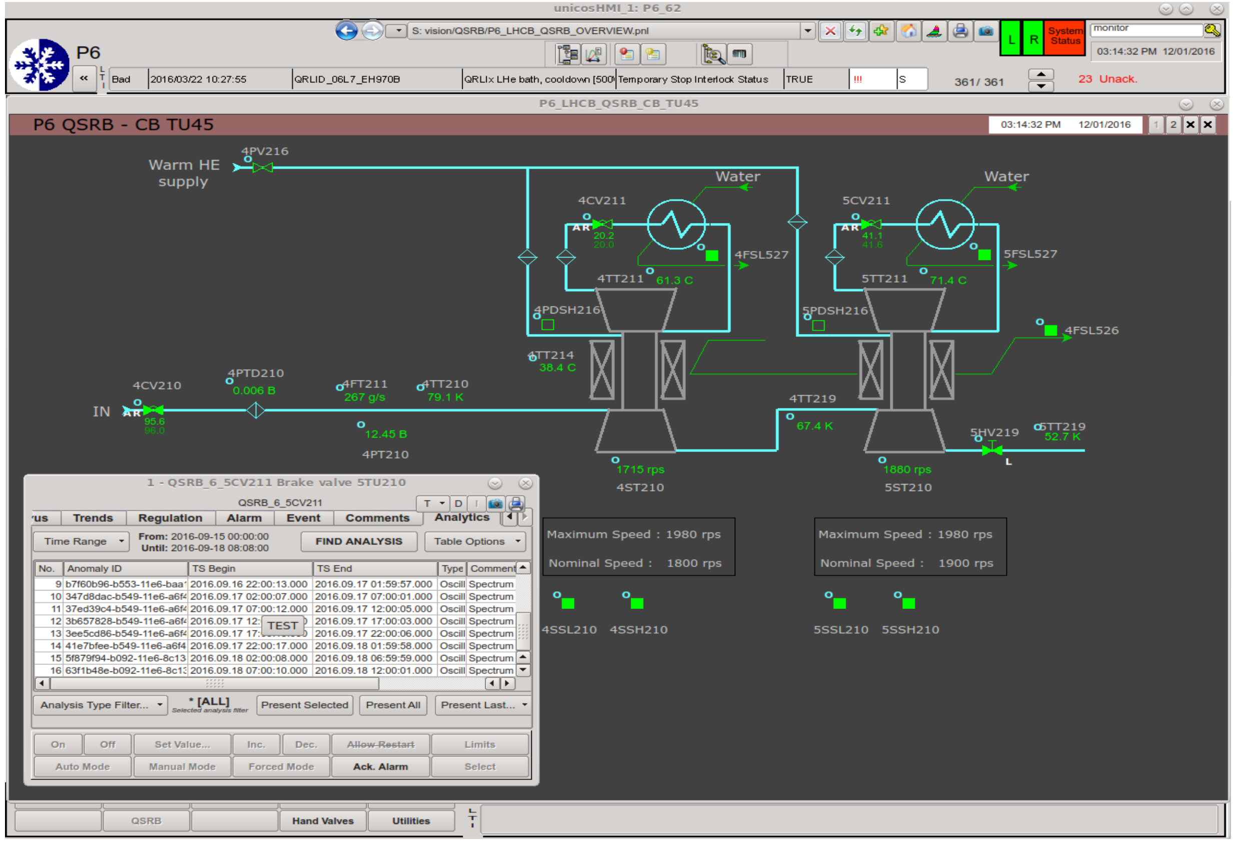
Oscillation detection on Spark

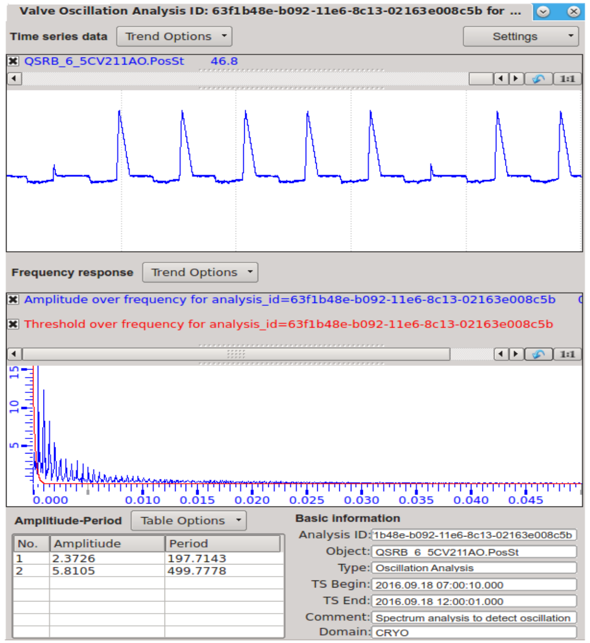




Oscillation detection & WinCC OA

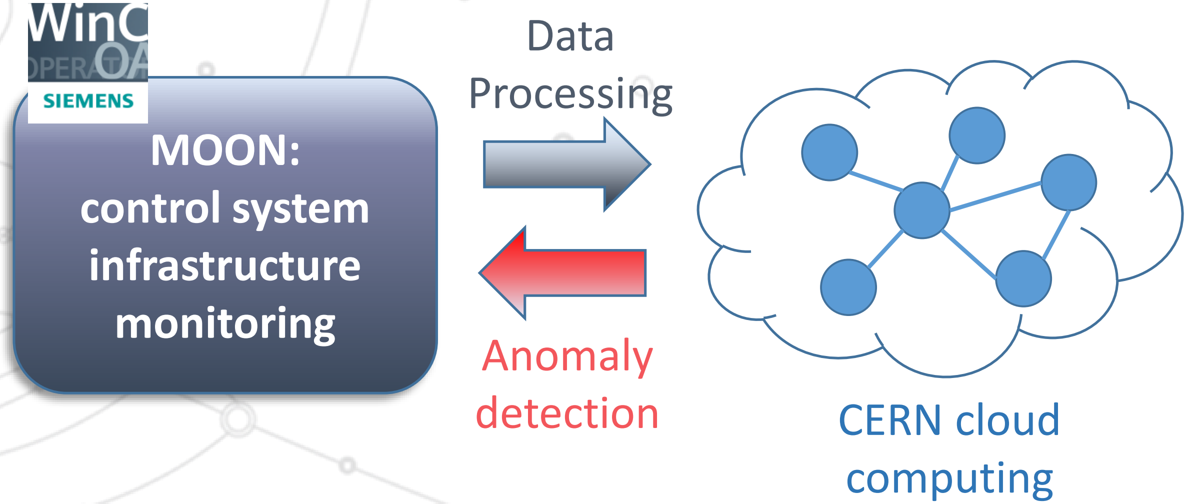
- Status:
  - Working prototype
  - Testing
- Next steps:
  - Extension for custom analysis types
  - Compatibility with WinCC OA 3.15
  - User Documentation



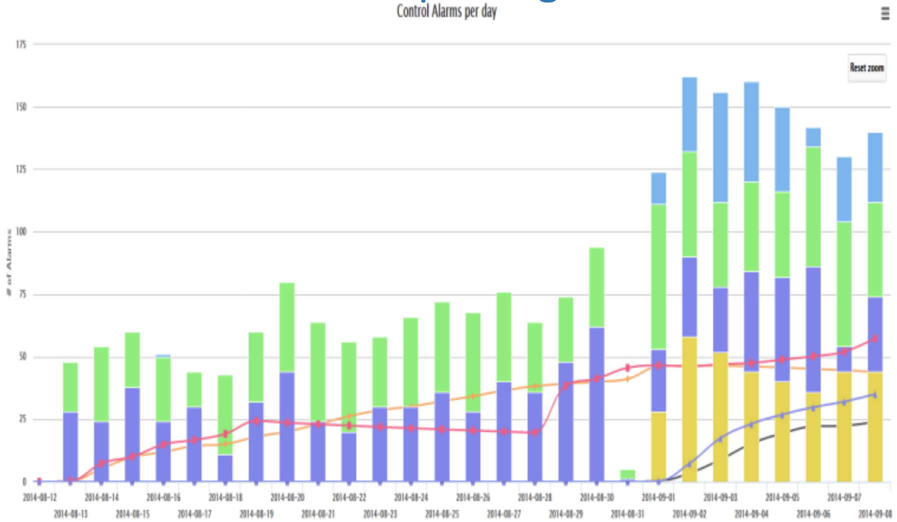


Online analysis of control alarms

- Alarms analysis to detect anomalies or abnormal behaviors for thousands of devices
- Events sequence mining
  - to understand the alarms' dependencies
  - for short term forecast
- Threshold learning algorithm and outliers detection techniques
  - Based on alarms' distribution
  - Parallelization using the CERN OpenStack cluster
- Graphical visualization of the anomalies/outliers



Web Reporting

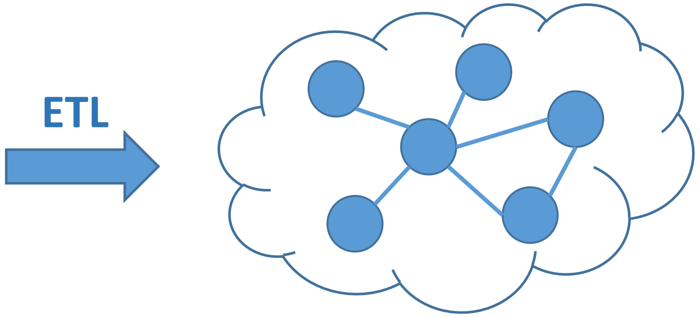


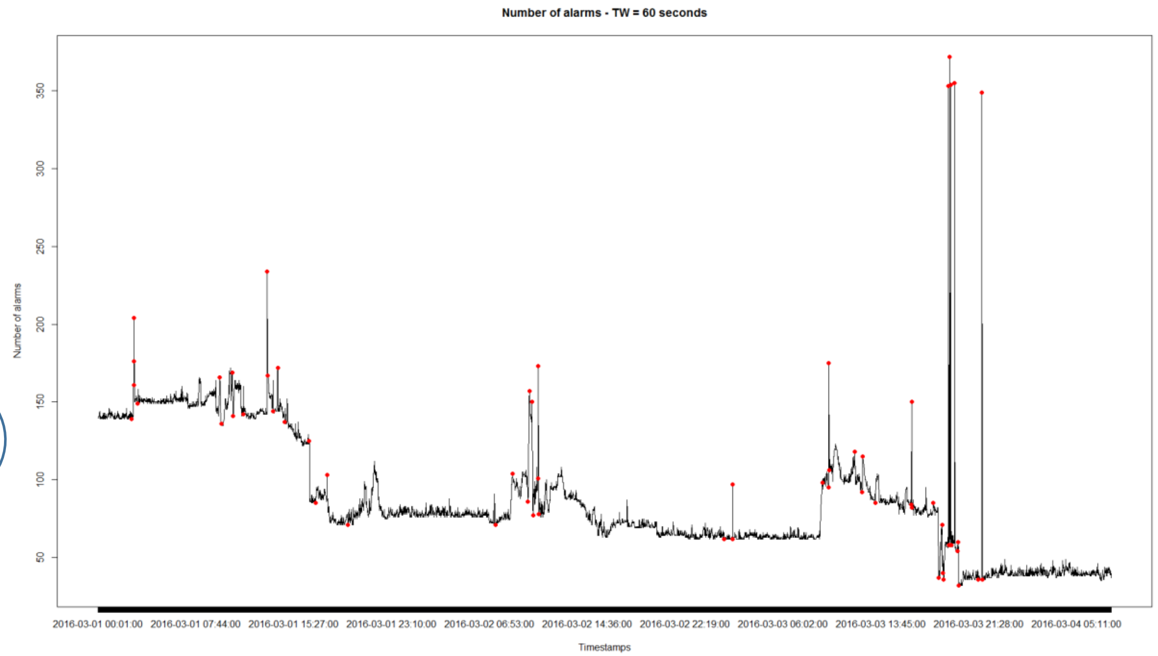
Anomaly detection of control process variables based on custom indexes

- Overview of the system through a list of indicators:
  - # / Average(#) of Alarms per Time Window
  - Integration
  - System Under Alarm
  - Probability of Finding Alarm
  - Frequency / Average of Frequency
  - Instability
  - Relative Strength
  - Regularity

- Analysis at different granularity: device, tag, level
- Identify significant changes in the data
- Trending analysis and forecast (on-going)

CERN cloud computing

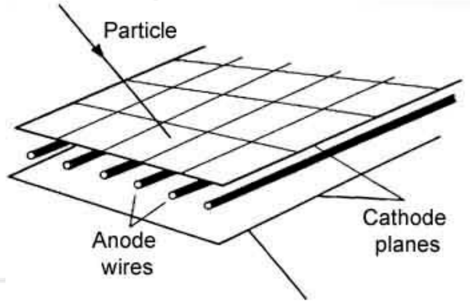


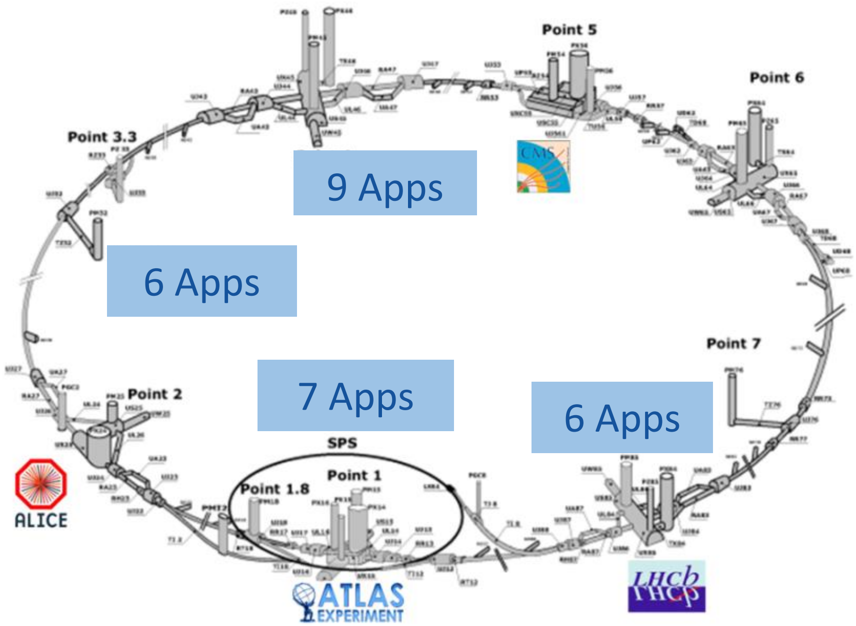


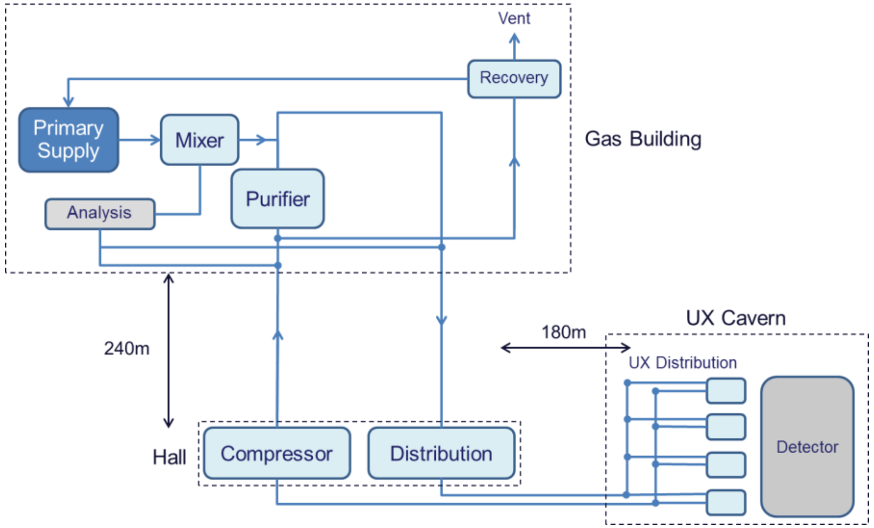
Fault diagnosis (off-line)

- Root cause analysis for control alarms avalanches (GAS system)
- Anomaly detection by sensors data mining

An example:
Gas control system @CERN

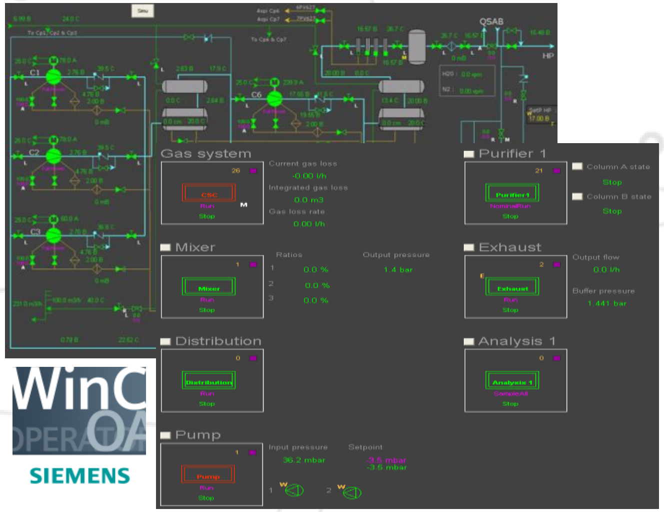






- 28 gas systems deployed around LHC
- 4 Data Server, 51 PLCs (29 for process control, 22 for flow-cells handling)
- Essential for particle detection
- Reliability and stability are critical
  - Any variation in the gas composition can affect the accuracy of the acquired data
- ~18 000 physical sensors / actuators

Alarm flooding problem



Domino effect

Short	Local Time	Alias	Description	Domain	Nature	Name	Value
W	2013.09.27 15:49:37.810	CMSCSC_Di_61InPresAl	PTxx24 - Rack 61 input	CSC_Details		PTxx24 - Rack 61 input pres	FALSE
W	2013.09.27 15:49:42.890	CMSCSC_Di_68InPresAl	PTxx24 - Rack 68 input	CSC_Details		PTxx24 - Rack 68 input pres	FALSE
W	2013.09.27 15:49:42.890	CMSCSC_Di_70InPresAl	PTxx24 - Rack 70 input	CSC_Details		PTxx24 - Rack 70 input pres	FALSE
W	2013.09.27 15:49:42.890	CMSCSC_Di_69InPresAl	PTxx24 - Rack 69 input	CSC_Details		PTxx24 - Rack 69 input pres	FALSE
W	2013.09.27 15:49:42.890	CMSCSC_Di_67InPresAl	PTxx24 - Rack 67 input	CSC_Details		PTxx24 - Rack 67 input pres	FALSE
W	2013.09.27 15:49:43.090	CMSCSC_Di_63InPresAl	PTxx24 - Rack 63 input	CSC_Details		PTxx24 - Rack 63 input pres	FALSE
W	2013.09.27 15:49:43.090	CMSCSC_Di_64InPresAl	PTxx24 - Rack 64 input	CSC_Details		PTxx24 - Rack 64 input pres	FALSE
W	2013.09.27 15:49:43.090	CMSCSC_Di_65InPresAl	PTxx24 - Rack 65 input	CSC_Details		PTxx24 - Rack 65 input pres	FALSE
W	2013.09.27 15:52:09.900	CMSCSC_Di_69OutPresFAA	PTxx26 - Rack 69 far out	CSC_Details		PTxx26 - Rack 69 far output	TRUE
W	2013.09.27 15:52:09.900	CMSCSC_Di_66OutPresAl	PTxx25 - Rack 66 output	CSC_Details		PTxx25 - Rack 66 output pre	TRUE
W	2013.09.27 15:52:09.900	CMSCSC_Di_69OutPresAl	PTxx25 - Rack 69 output	CSC_Details		PTxx25 - Rack 69 output pre	TRUE
W	2013.09.27 15:52:09.900	CMSCSC_Di_70OutPresAl	PTxx25 - Rack 70 output	CSC_Details		PTxx25 - Rack 70 output pre	TRUE
W	2013.09.27 15:52:09.900	CMSCSC_Di_70OutPresFAA	PTxx26 - Rack 70 far out	CSC_Details		PTxx26 - Rack 70 far output	TRUE
W	2013.09.27 15:52:09.900	CMSCSC_Di_67OutPresFAA	PTxx26 - Rack 67 far out	CSC_Details		PTxx26 - Rack 67 far output	TRUE
W	2013.09.27 15:52:09.900	CMSCSC_Di_66OutPresFAA	PTxx26 - Rack 66 far out	CSC_Details		PTxx26 - Rack 66 far output	TRUE
W	2013.09.27 15:52:09.900	CMSCSC_Di_67OutPresAl	PTxx25 - Rack 67 output	CSC_Details		PTxx25 - Rack 67 output pre	TRUE
W	2013.09.27 15:52:09.900	CMSCSC_Di_68OutPresAl	PTxx25 - Rack 68 output	CSC_Details		PTxx25 - Rack 68 output pre	TRUE
W	2013.09.27 15:52:09.900	CMSCSC_Di_68OutPresFAA	PTxx26 - Rack 68 far out	CSC_Details		PTxx26 - Rack 68 far output	TRUE
W	2013.09.27 15:52:10.440	CMSCSC_Di_64OutPresFAA	PTxx26 - Rack 64 far out	CSC_Details		PTxx26 - Rack 64 far output	TRUE
W	2013.09.27 15:52:10.440	CMSCSC_Di_64OutPresAl	PTxx25 - Rack 64 output	CSC_Details		PTxx25 - Rack 64 output pre	TRUE
W	2013.09.27 15:52:10.440	CMSCSC_Di_65OutPresAl	PTxx25 - Rack 65 output	CSC_Details		PTxx25 - Rack 65 output pre	TRUE
W	2013.09.27 15:52:10.440	CMSCSC_Di_65OutPresFAA	PTxx26 - Rack 65 far out	CSC_Details		PTxx26 - Rack 65 far output	TRUE
W	2013.09.27 15:52:10.440	CMSCSC_Di_63OutPresAl	PTxx25 - Rack 63 output	CSC_Details		PTxx25 - Rack 63 output pre	TRUE
W	2013.09.27 15:52:10.440	CMSCSC_Di_61OutPresAl	PTxx25 - Rack 61 output	CSC_Details		PTxx25 - Rack 61 output pre	TRUE
W	2013.09.27 15:52:10.440	CMSCSC_Di_63OutPresFAA	PTxx26 - Rack 63 far out	CSC_Details		PTxx26 - Rack 63 far output	TRUE
W	2013.09.27 15:52:10.440	CMSCSC_Di_61OutPresFAA	PTxx26 - Rack 61 far out	CSC_Details		PTxx26 - Rack 61 far output	TRUE
A	2013.09.27 15:52:12.890	CMSCSC_Di_66OutPresAl	PTxx25 - Rack 66 output	CSC_Details		PTxx25 - Rack 66 output pre	TRUE
A	2013.09.27 15:52:12.890	CMSCSC_Di_66OutPresFAA	PTxx26 - Rack 66 far out	CSC_Details		PTxx26 - Rack 66 far output	TRUE
Bad	2013.09.27 15:52:12.950	CMSCSC_Di_DiRack66PCO	Distribution rack 66 PCO	CSC_Details		Full Stop Alarm Status	TRUE
Bad	2013.09.27 15:52:12.950	CMSCSC_Di_DiRack61PCO	Distribution rack 61 PCO	CSC_Details		Full Stop Alarm Status	TRUE
A	2013.09.27 15:52:13.370	CMSCSC_Di_61OutPresFAA	PTxx26 - Rack 61 far out	CSC_Details		PTxx26 - Rack 61 far output	TRUE
A	2013.09.27 15:52:13.370	CMSCSC_Di_61OutPresAl	PTxx25 - Rack 61 output	CSC_Details		PTxx25 - Rack 61 output pre	TRUE
A	2013.09.27 15:52:32.110	CMSCSC_Di_AlarmInRack66	Some alarms in rack 66	CSC_Details		Rack 66 alarm	TRUE
A	2013.09.27 15:52:32.110	CMSCSC_Di_AlarmInRack61	Some alarms in rack 61	CSC_Details		Rack 61 alarm	TRUE
A	2013.09.27 15:57:47.130	CMSCSC_Xh_AtmPrSensAll	PT0101 - Atmospheric pre	CSC_Details		PT0101 - Atmospheric press	TRUE

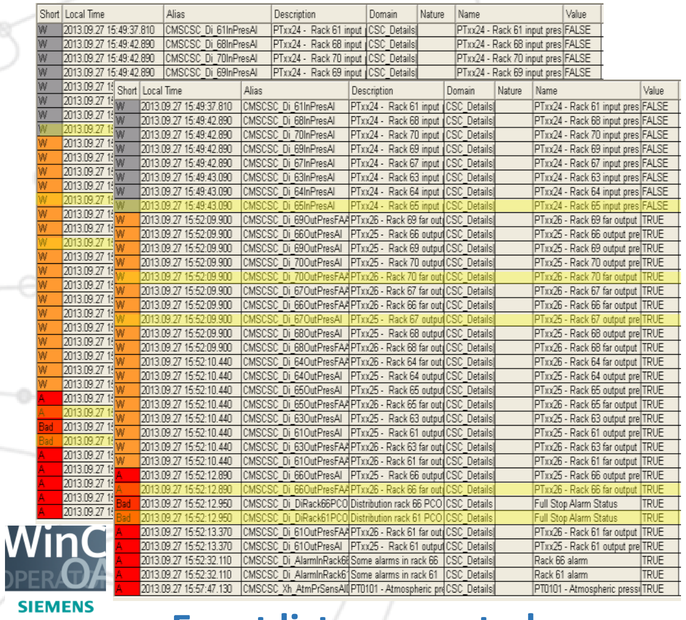
Fault in the distribution system

Alarms flooding

- **Diagnosing a fault is complex:** it may take weeks!
  - Alarms flooding: a single fault can generate up to a thousand of events
  - Number of different sequences:

    ~$6x10^{297}$ from: n!/(n-k)! , n=max seq. length, k=n/10
  - A single fault can stop the whole control process
  - The 1^{st} alarm is not necessarily the most relevant for the diagnosis
  - Alarm generation depends on the system status

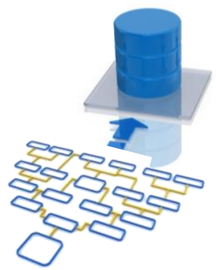
Events stream analysis



Event lists generated by the same fault

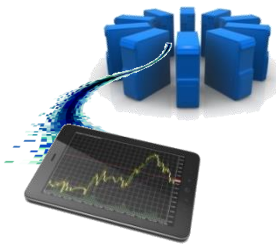
Data

Analyze



Identify and detect fault / abnormal pattern for Diagnosis and Prognostics based on domain knowledge

Learn



Provide experts with Root-cause and Gap Analysis using Rules and Patterns Mining

Diagnose

Forecasts, Trends and Early-Warnings to increase Operating Hours

Sequence: Confidence: 83.3 % / Appearance count: 5

CMSCSC_Di_62PRegAl | Alarm Unacknowledged | Rising
CMSC
CMSC
CMSC
CMSC
CMSC
CMSC
CMSC
CMSC
CMSC

Sequence: Confidence: 100.0 % / Appearance count: 6

CMSCSC_Di_62PRegAl | Alarm Unacknowledged | Rising
CMSCSC_Di_62PRegAl | Position Status (HH-LL) | Rising

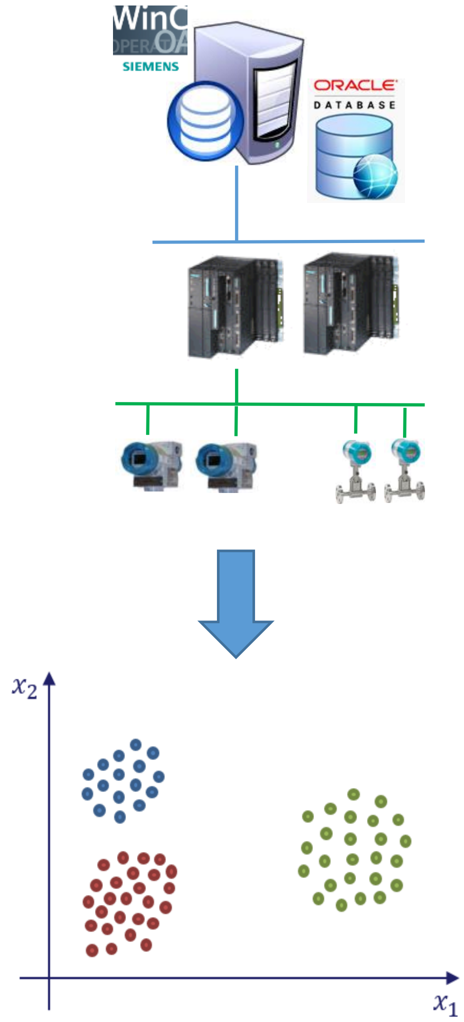
CMSCSC_Di_YC60995 | Auto Off/Close Request Status | Falling
CMSCSC_Di_YC60995 | Auto On/Open Request Status | Rising
CMSCSC_Di_YC60995 | Off/Closed Status | Falling
CMSCSC_Di_YC60995 | On/Opened Status | Rising
CMSCSC_Di_YC60995 | Output Order Value Status | Rising

Pattern AA B A A B → **Alarm**

X T C D F A A E D N D B K D F A A B K D

Anomaly detection by sensors data mining

- Goal: Detect abnormal or unforeseen system behaviours
- Possible issues:
  - Sensors faults/glitches
  - Hardware failures/degradations
  - False measurements
  - Wrong tuning/structure
  - …
- Sensors mining to learning:
  - Logical relations
  - Physical relations
- Challenges:
  - Normal/anomalous boundaries are not precise
  - Different application domains/systems
  - Mostly unsupervised training
  - Dynamic system => dynamic model
  - Different types of anomaly
  - Noise and duration of an anomaly



Machine learning algorithms for anomaly detection in Cryo

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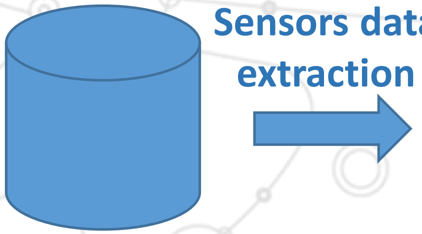
LHC Logging Service

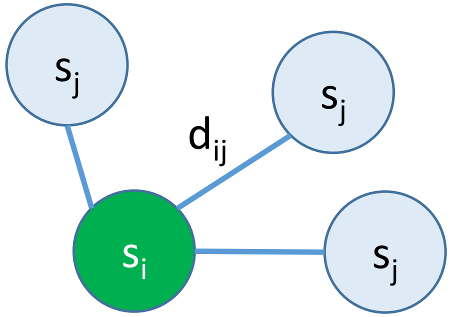


Sensors data extraction

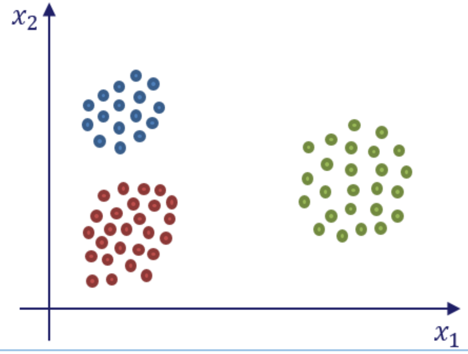
Learning phase

- Building a model based on historical data
- 3 different algorithms
  - Correlation index and KNN-graph
  - K-Mean clustering and probability model
  - Statistics expert-based model

$$E(d_i) = \sum_{j=1}^{k} d_{ij} * P(j|i)$$

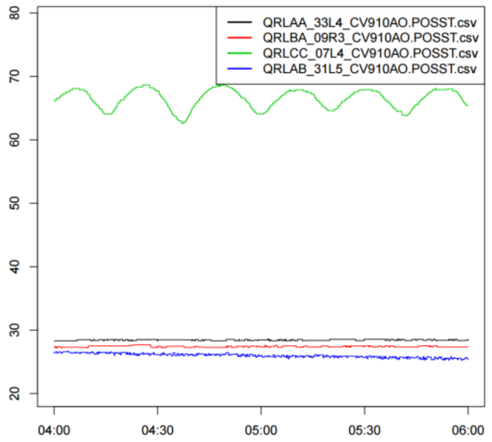


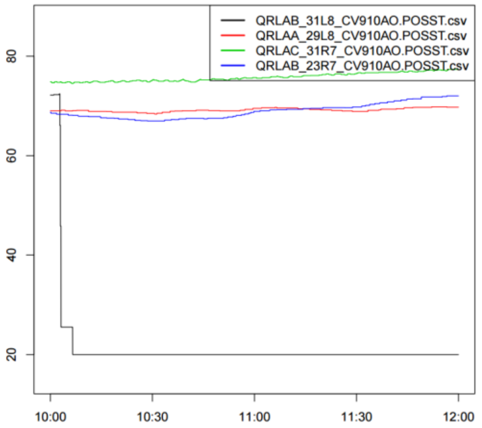
$$\min \frac{1}{C}\sum_{k=1}^{C} \max_{l\neq k}\left\{\frac{\frac{\sum_i \| x_i - c_k \|}{N_k} + \frac{\sum_i \| x_i - c_l \|}{N_l}}{\| c_k - c_l \|}\right\}$$



Anomaly detection

- Use the previous model to detect anomalies
- On-line analysis over a time window of 1 day
- Continuous analysis against thousands of sensors



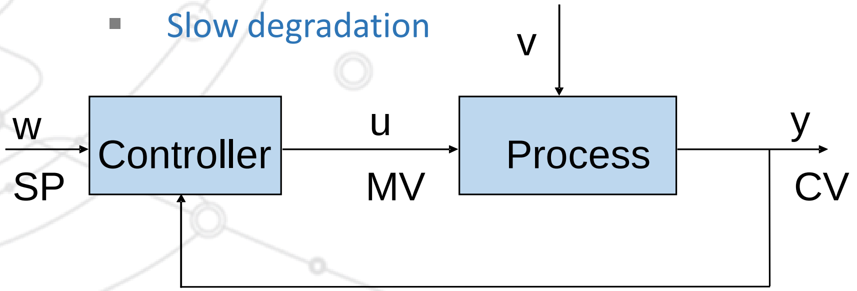


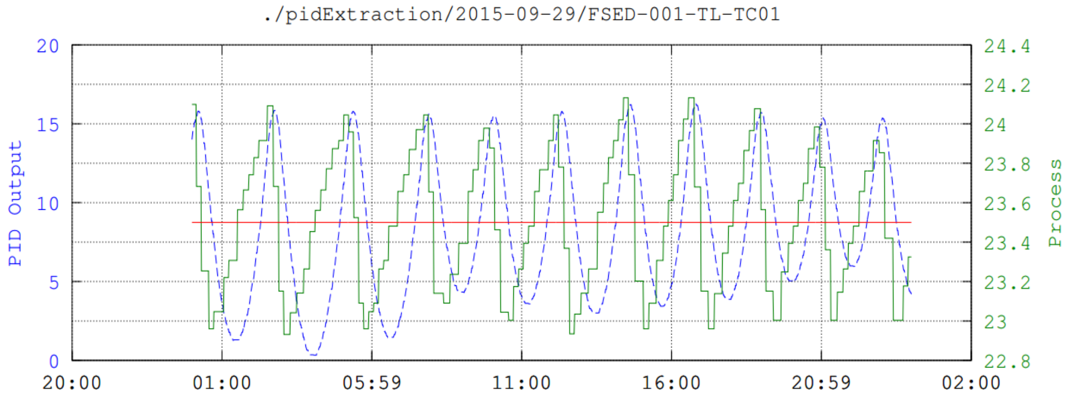
Engineering design

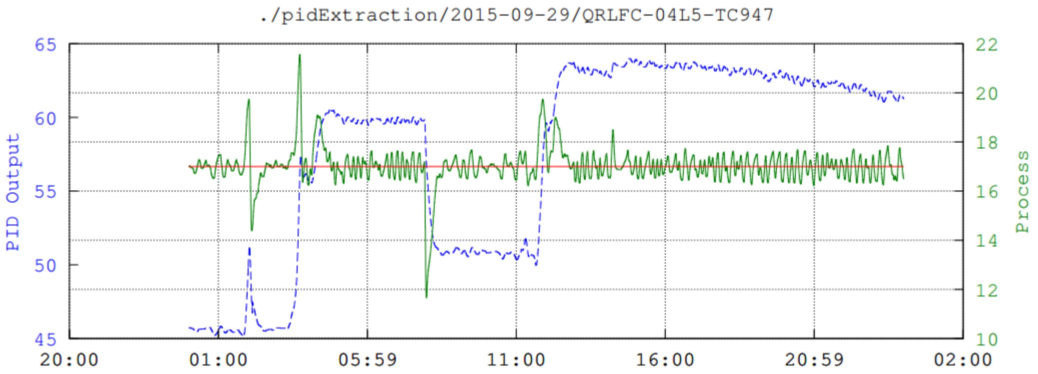
- PID supervision (CRYO, CV)
- Recommendation system for WinCC OA users (PSEN)

Evaluation of PID supervision

- **In collaboration with the University of Valladolid**
  Based on: "Performance monitoring of industrial controllers based on the predictability of controller behaviour", R. Ghraizi, E. Martinez, C. de Prada
- **PID performance has an impact on:**
  - Process security
  - Quality of physics
  - Maintenance (stress on the equipment)
- **Issues:**
  - Many sources of faults/malfunctions
  - System status dependency
  - External disturbances/factors
  - Bad tuning
  - Wrong controller type/structure
  - Slow degradation







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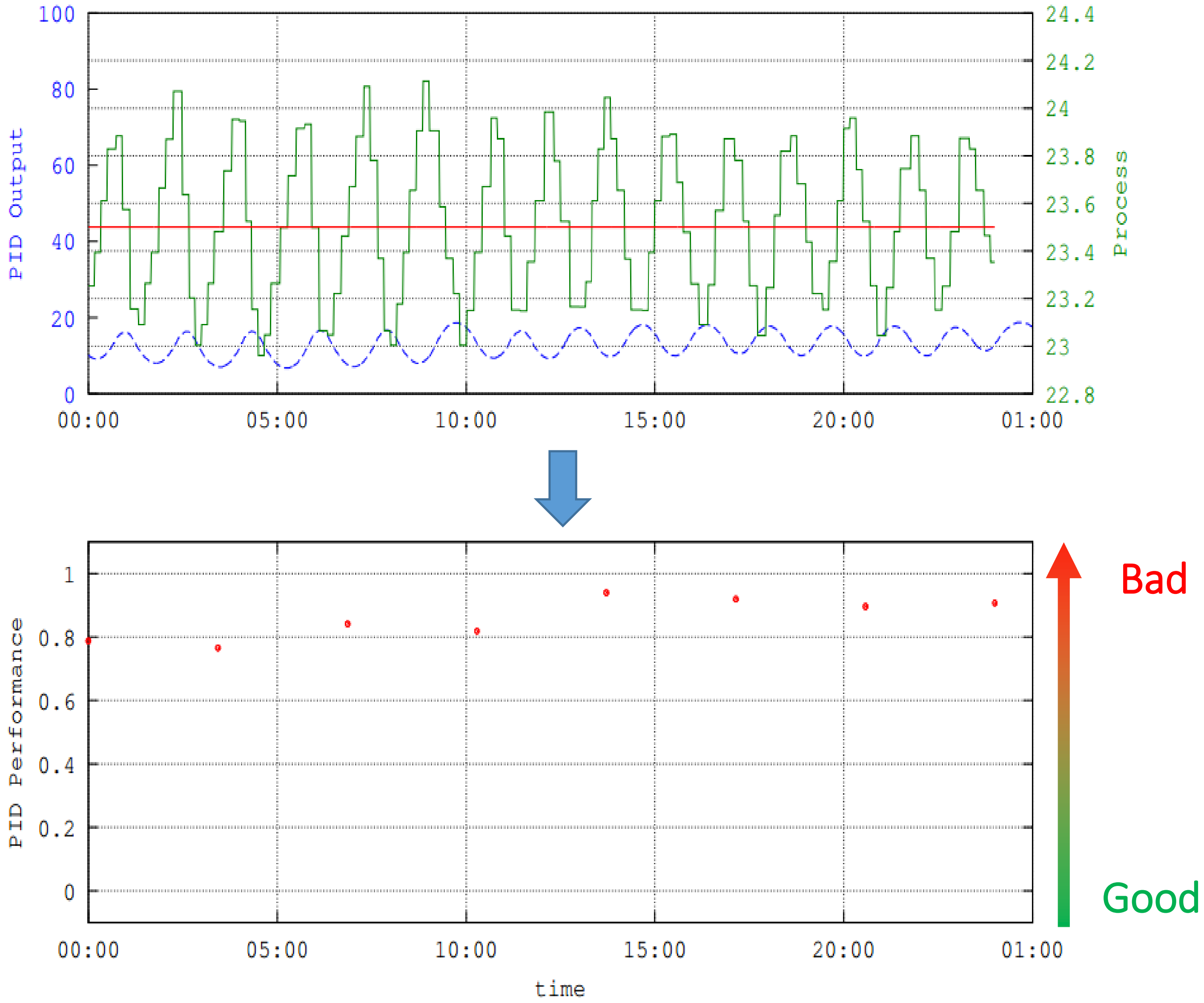
PID supervision Ex#1

PID anomaly detection:

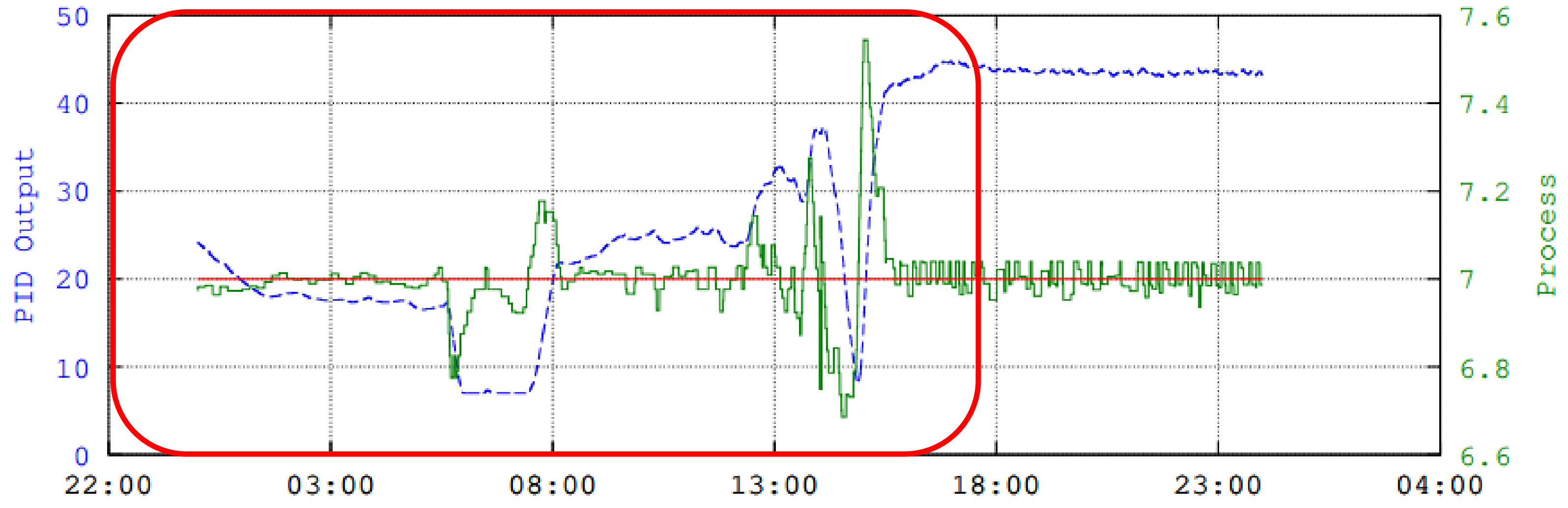
- Learning each PID model from the historical data
- Extraction of similar PID models
- Comparison of PID behaviours:
  - on the single PID level
  - similar PID

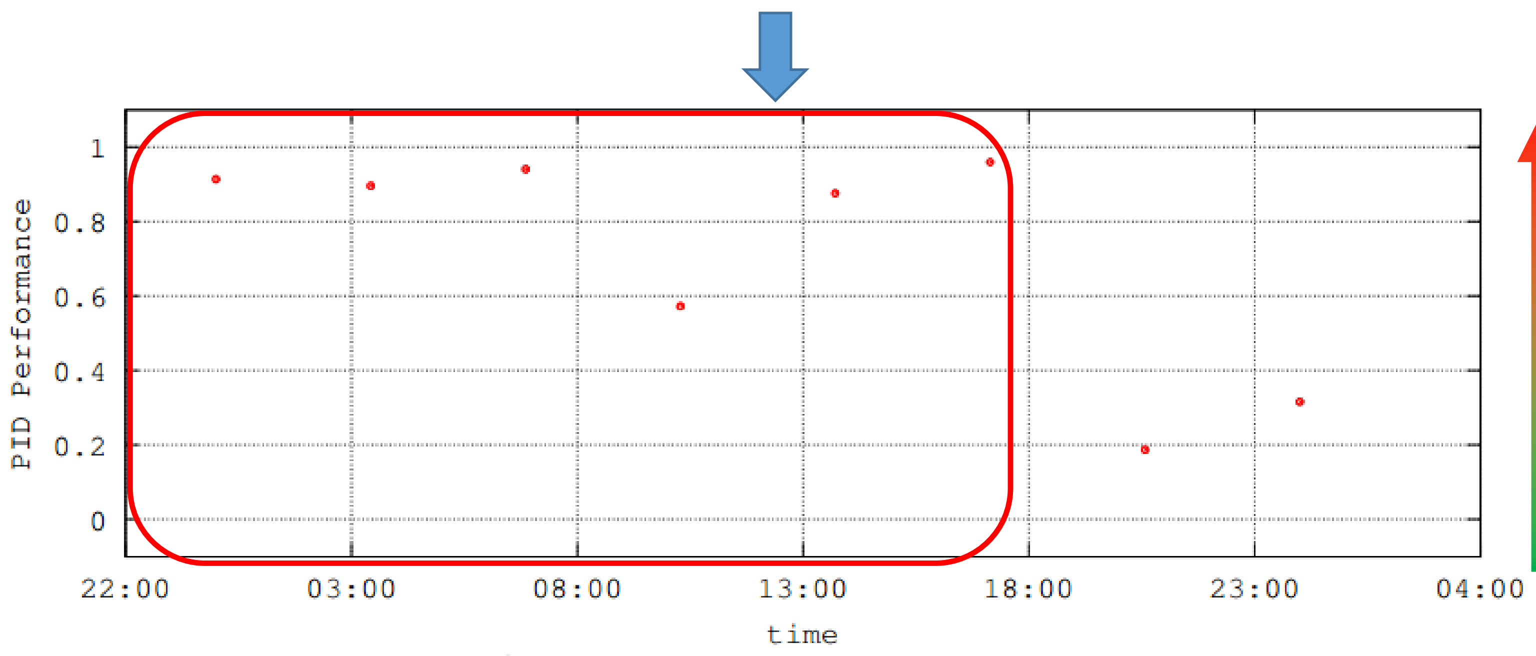
Efficiency of control process:

- Comparison of PID performances
- Time/actions taken/energy consumed to reach steady points
- Stability of the controlled variable



PID supervision Ex#2

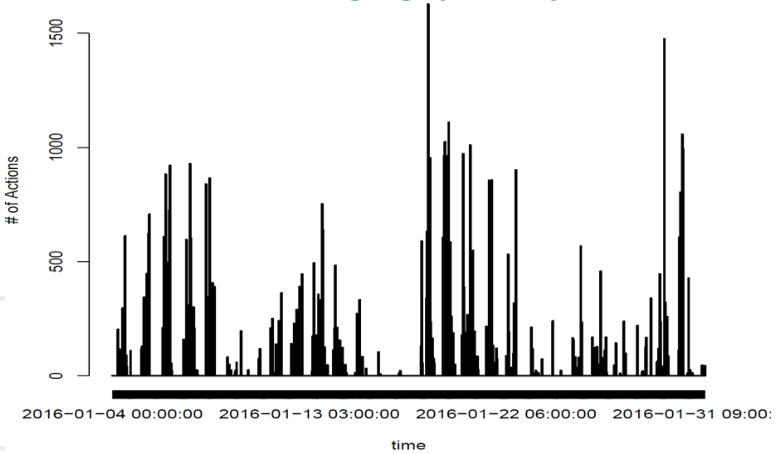




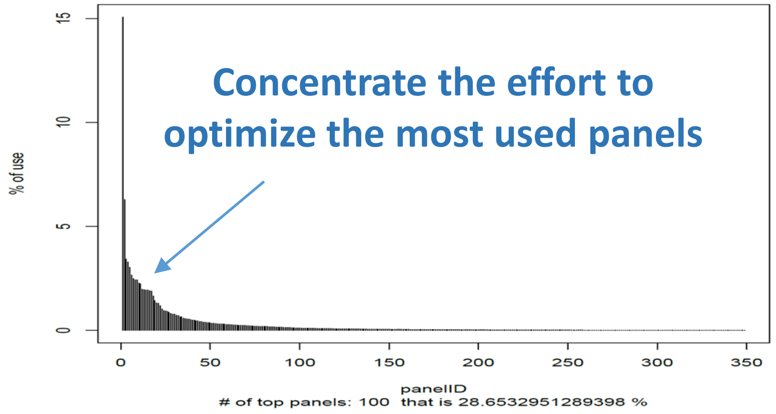
Recommendation system for WinCC OA users

Users' actions extraction

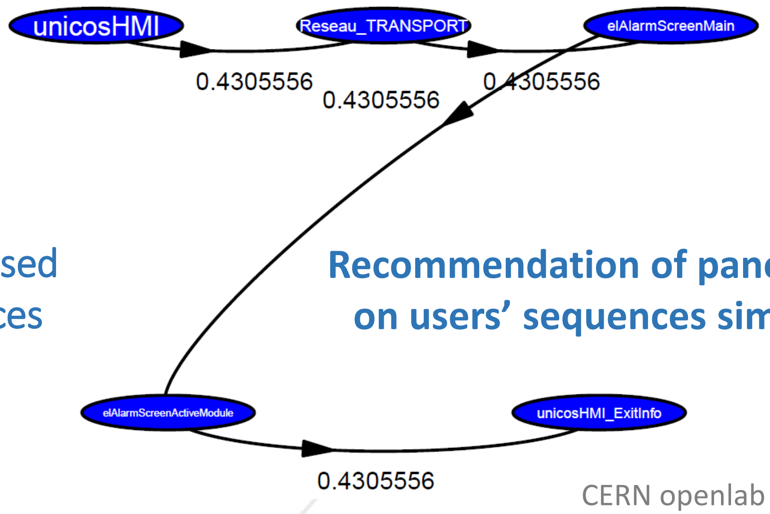
Users' usage gap analysis



Normalized distribution of panels usage



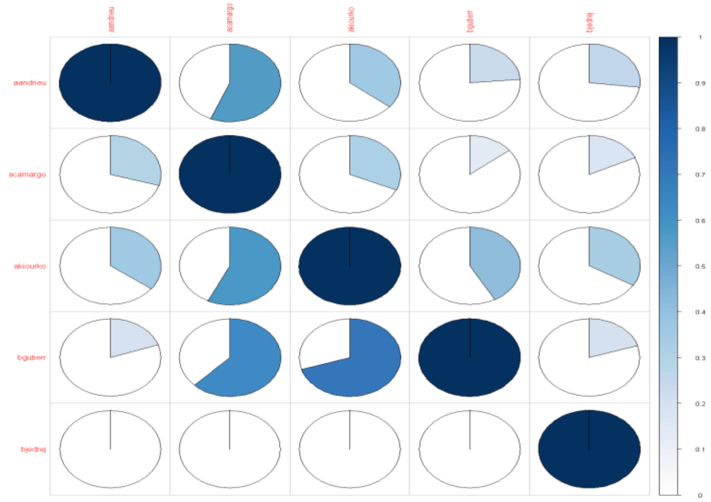
Users' frequent sequences



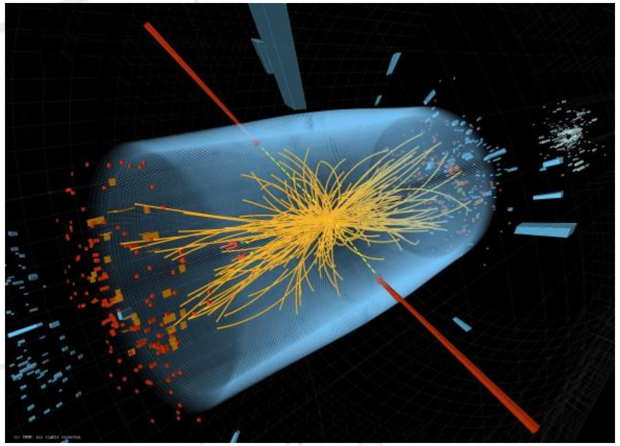
Recommendation of panels based on the specific users' sequences

Recommendation of panels based on users' sequences similarities

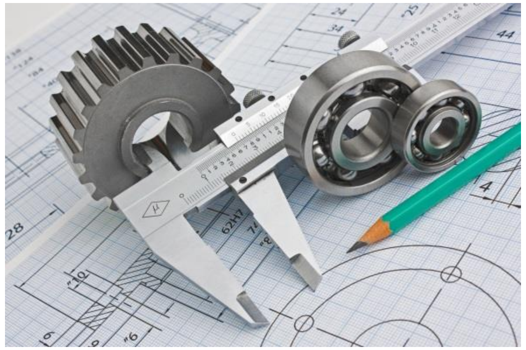
Jaccard Sequences Similarity



Data Analytics Benefits



- **Increased System Reliability**
  - Minimized forced outages
- **Complete data analysis**
  - Reduced service effort: weeks → hours
- **24/7 Expert Knowledge Availability**
  - One central knowledge base



Operation support

- Big data visualization
- Forecast system status and take proper actions in time
- Prevent possible faults and system downtime

Diagnosis support

- Identify root causes
- More accurate analysis
- Accelerate analysis From weeks to hours
- Identify hidden patterns

Engineering support

- Evaluate and improve operational performance
- Increase reliability and efficiency by design
- Lead control system decisions

Use-cases: a partial list

- **Online monitoring**
  - Control System Health
  - Electrical power quality of service
  - Looking for heat in superconducting magnets
  - Oscillation in cryogenics valves
  - Discharge of superconducting magnets heaters
  - Trending and forecast of the control process behavior
  - Electron cloud heat load estimation
- **Faults diagnosis**
  - Anomalies in the process regulation
  - PLC anomalies
  - Data loss detection
  - Root-cause analysis for complex WinCC OA installations
  - Analysis of sensors functioning and data quality
  - Analysis of OPC-CAN middleware
  - Analysis of electrical power cuts
  - Cryogenic system breakdowns
- **Engineering design**
  - Electrical consumption forecast
  - Efficiency of electric network
  - Predictive maintenance of control systems elements
  - Predictive maintenance for control disks storage
  - Vibration analysis
  - Efficiency of control process
  - …