ML-based methodology for HPC facilities supervision

ISC HPC International Workshop on Monitoring and Operational Data Analytics (MODA23)

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Contents

Context

- TGCC computing center
  - Joliot-Curie supercomputer: 22 Petaflops
  - Topaze supercomputer: 8.8 Petaflops

- HPC facilities
  - Infrastructure temperature (compute nodes, fans, water circuit)
  - External temperature
  - Energy consumption (computation, facilities)
  - Water consumption
  - Fan rotation

→ Administrators need to check everything

Limitations

- Huge amount of information to process
- Increase of the number of heterogenous components
- Supervision is getting complex
  - ➢ **Anomalies are more difficult to detect**

Targets

- Better visualisation with automation
- Detection of abnormal behaviour
- *Reduction of energy consumption*

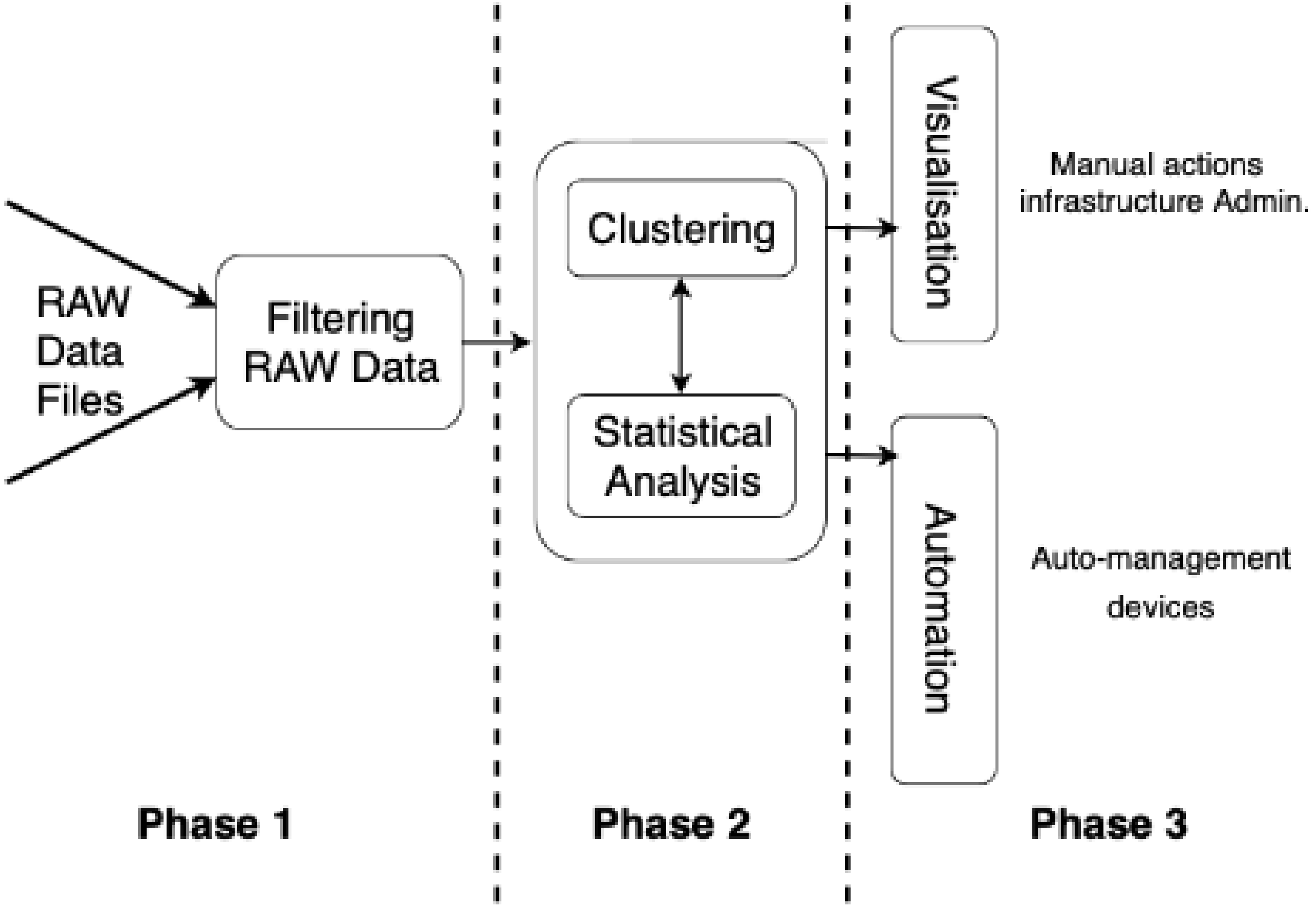
Related works

Works around AI for operational HPC:

- To predict anomalies/health status on hardware
- To predict workload intensity on HPC
- To predict energy consumption of HPC facilities

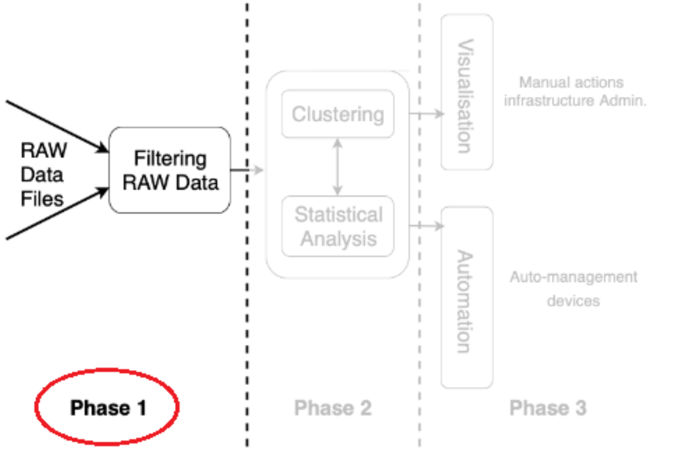
➢ But at our knowledge, none for consumption tuning around facilities

Workflow

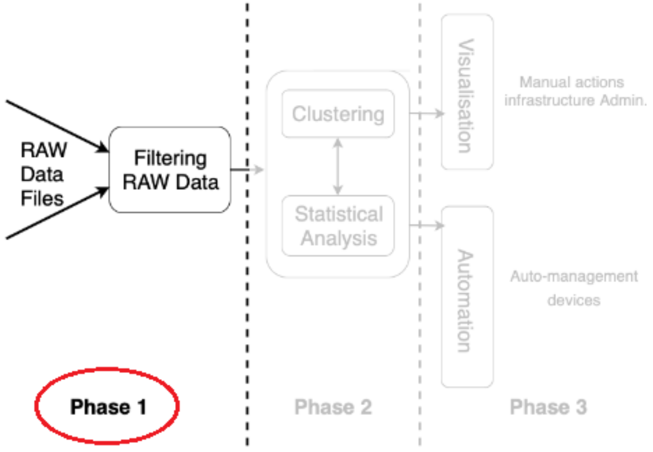

RAW
Data
Files
Filtering
RAW Data
Clustering
Statistical
Analysis
Visualisation
Automation
Manual actions
infrastructure Admin.
Auto-management
devices
Phase 1
Phase 2
Phase 3

Phase 1: Collecting and filtering raw data

- Raw data:
  - Two years of collected data
  - Frequency of one measurement per minute
  - **93 probes** from different devices & levels of the infrastructure



Phase 1: Collecting and filtering raw data

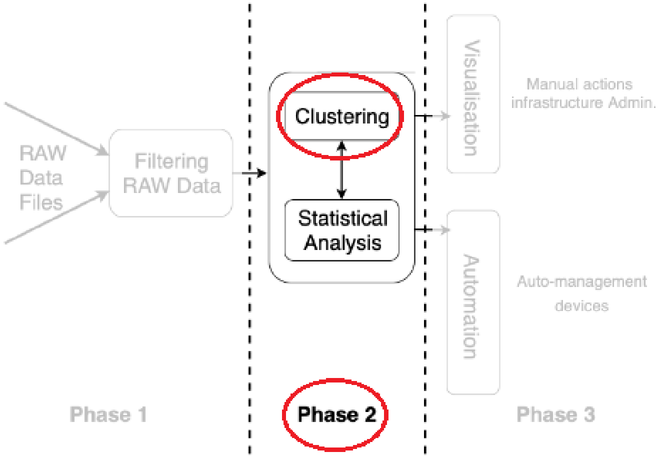


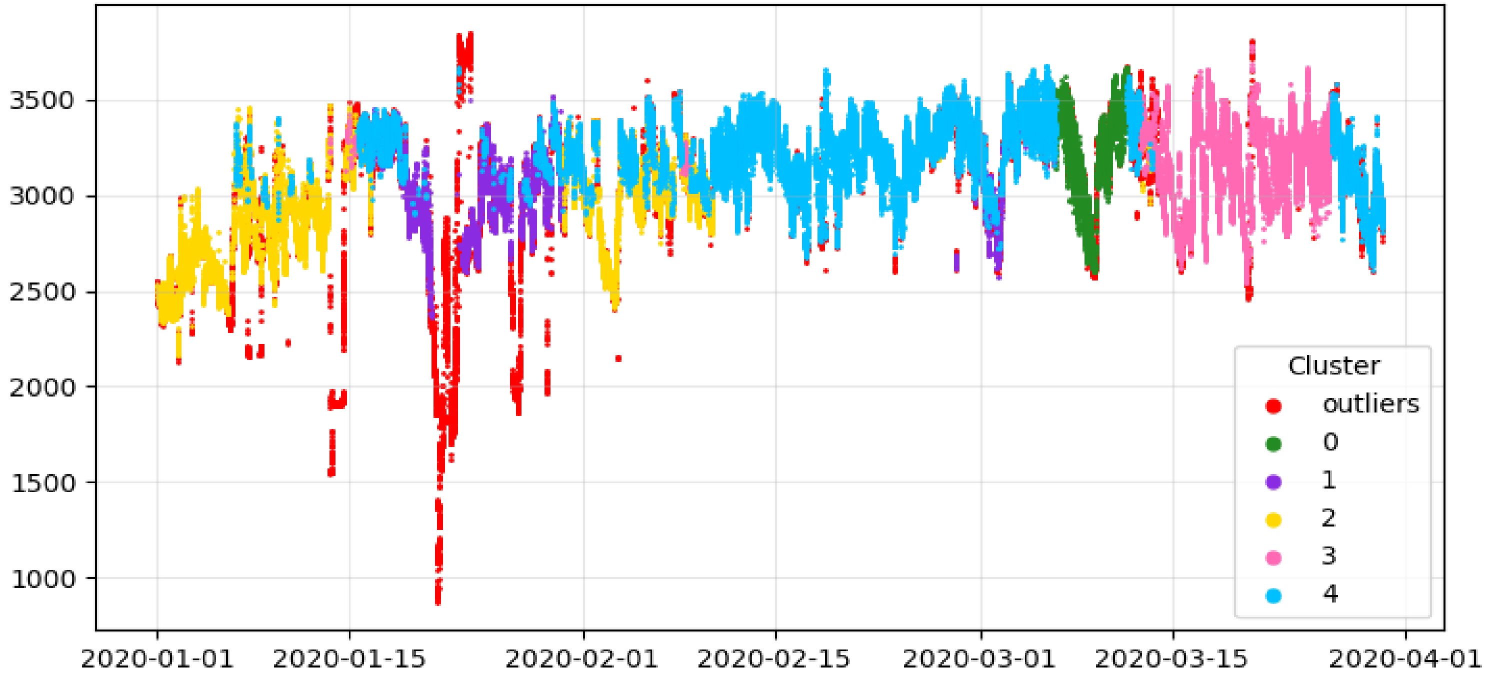
- Raw data:
  - Two years of collected data
  - Frequency of one measurement per minute
  - **93 probes** from different devices & levels of the infrastructure

- Filtered data:
  - Unreliable and incomplete data removed: **89 probes** finally retained
  - Data reduction factor of **4.5**: for 1 year **from 1.2GB to 264MB**
  - Focus on 1st quarter 2020

Phase 2: Clustering

- Target: grouping similar events into typical behaviors
- HDBSCAN as clustering method: based on cluster density, number of clusters auto-determined by setting a minimum density threshold

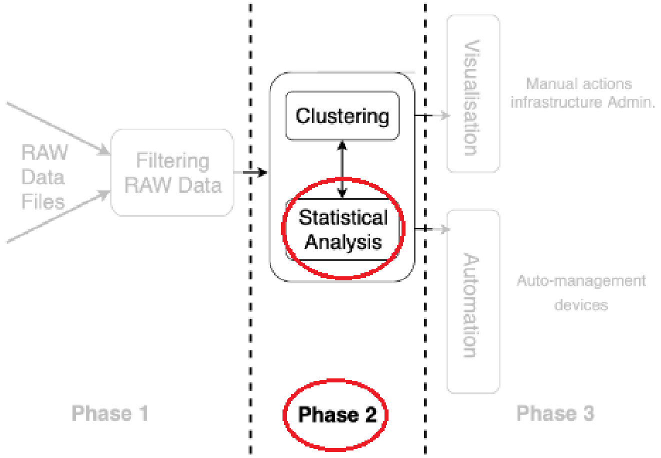


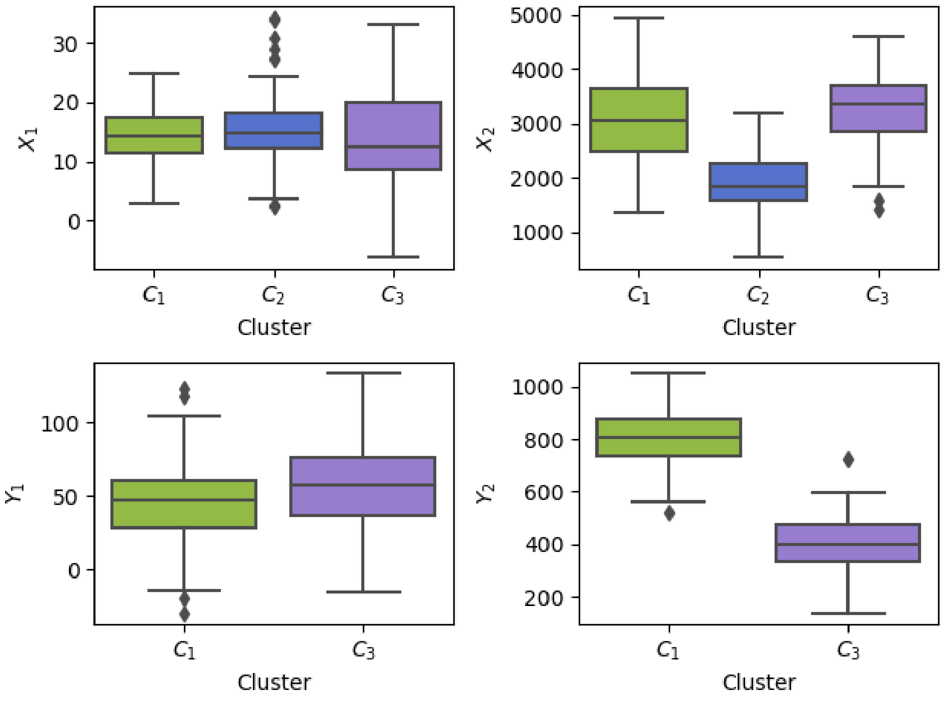


Power (kW) used by IT Q1 2020

Phase 2: Statistical analysis

- Identification of clusters with the same operating mode
  - Operating metrics X : external temperature and workload intensity





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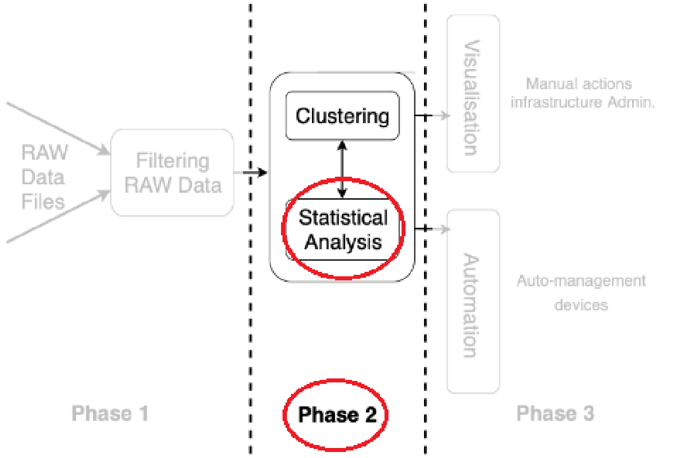
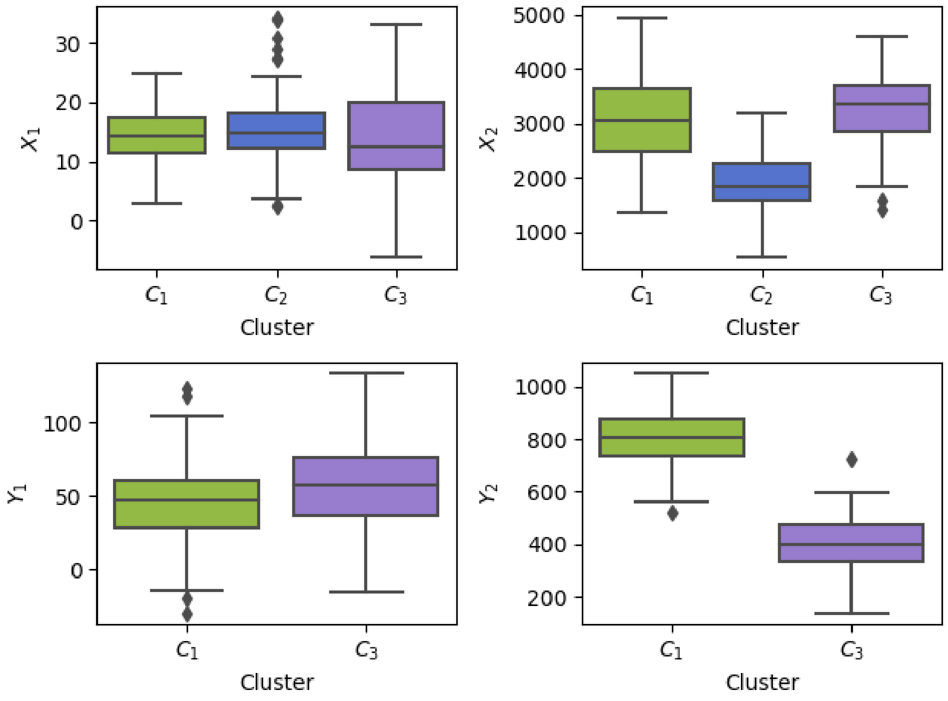




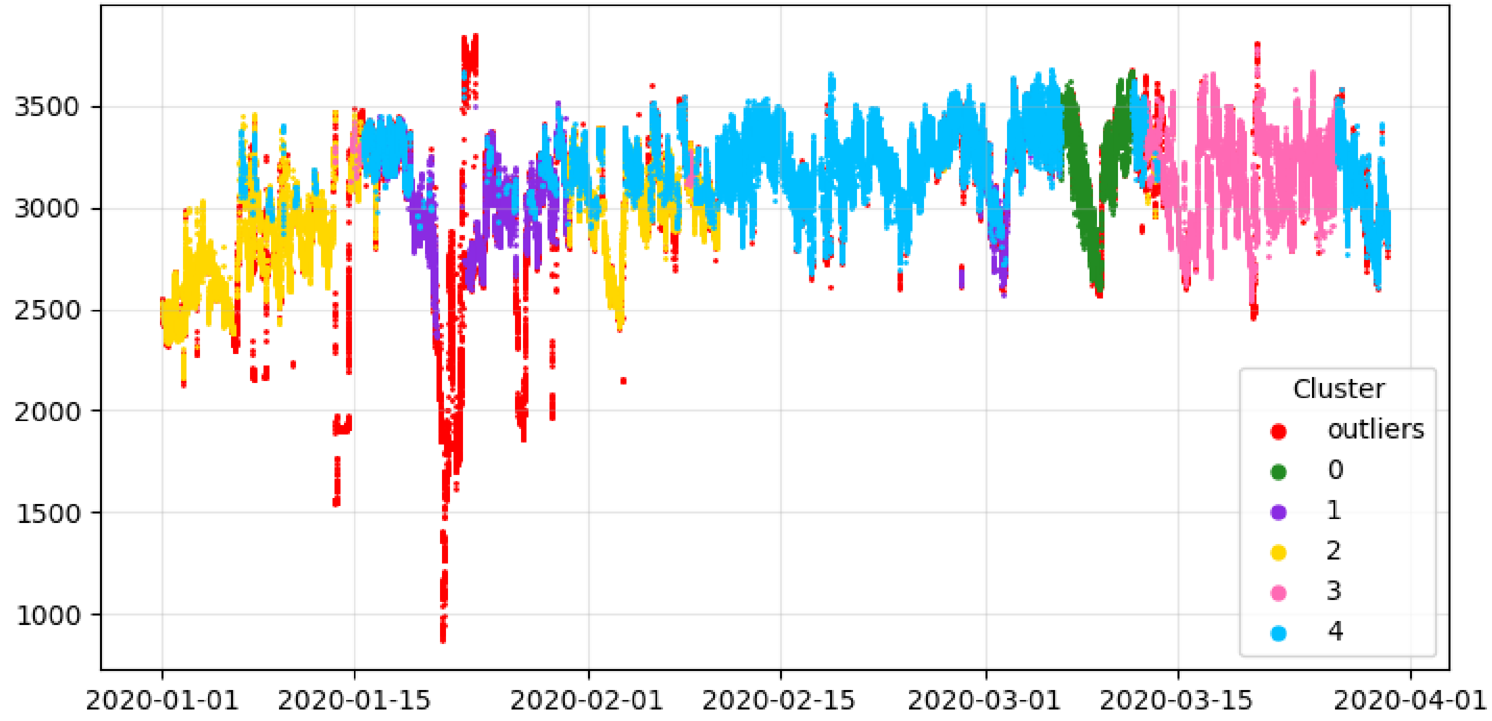
- Determination of the deviant metrics and their impact

Why are there 2 clusters in the same operating mode?

  - Calculation of the impact of each involved metric by measuring the gap between the quartiles of the 2 clusters

Phase 2: Statistical analysis — Application

- Identification of clusters with the same operating mode



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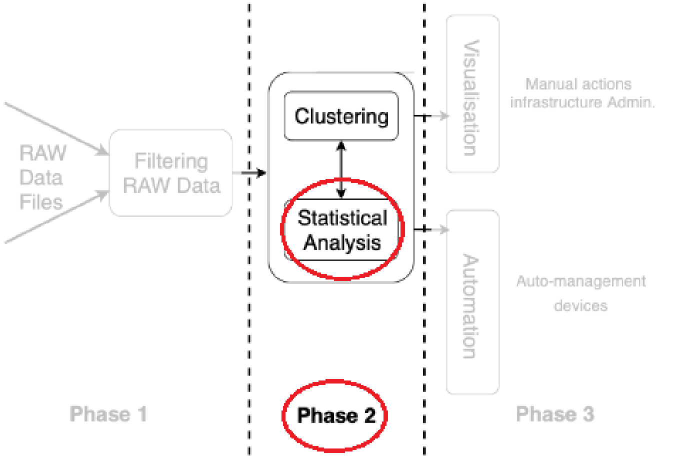

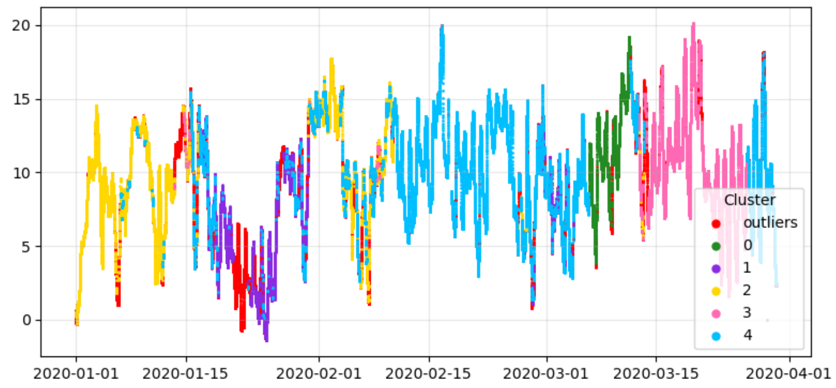

External temperature (°C) Q1 2020

➢ **Cluster 4 and 0 share the same operating mode**

Phase 2: Statistical analysis — Application

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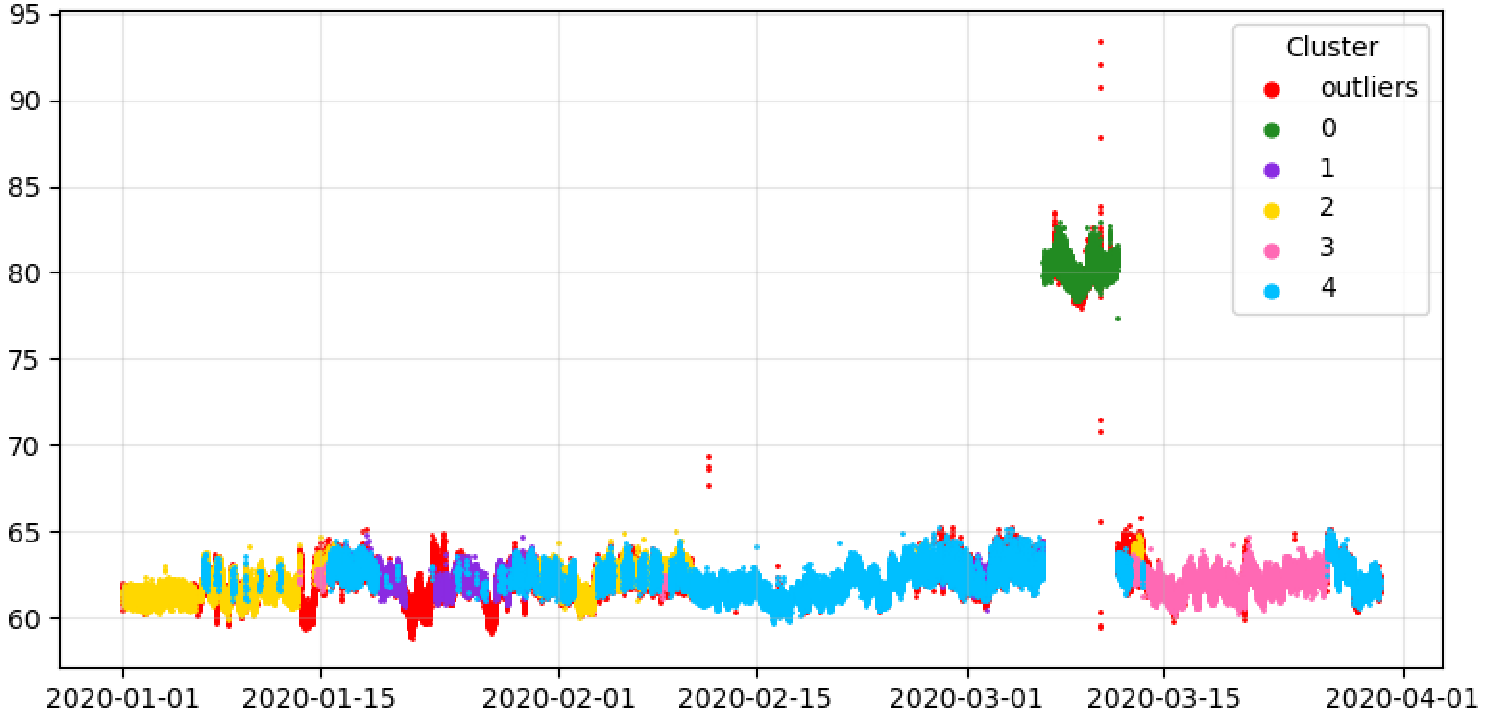
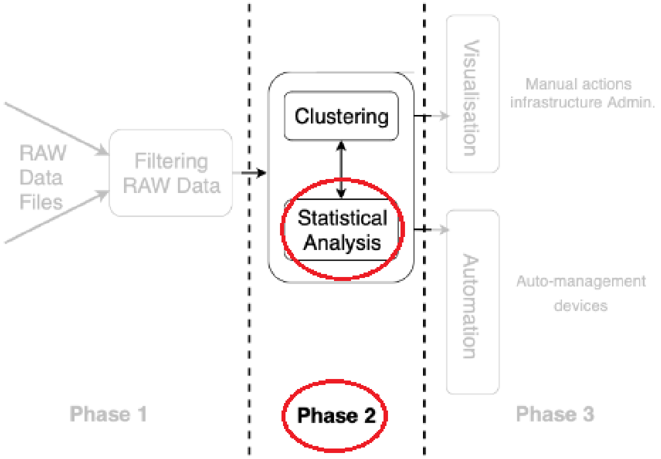
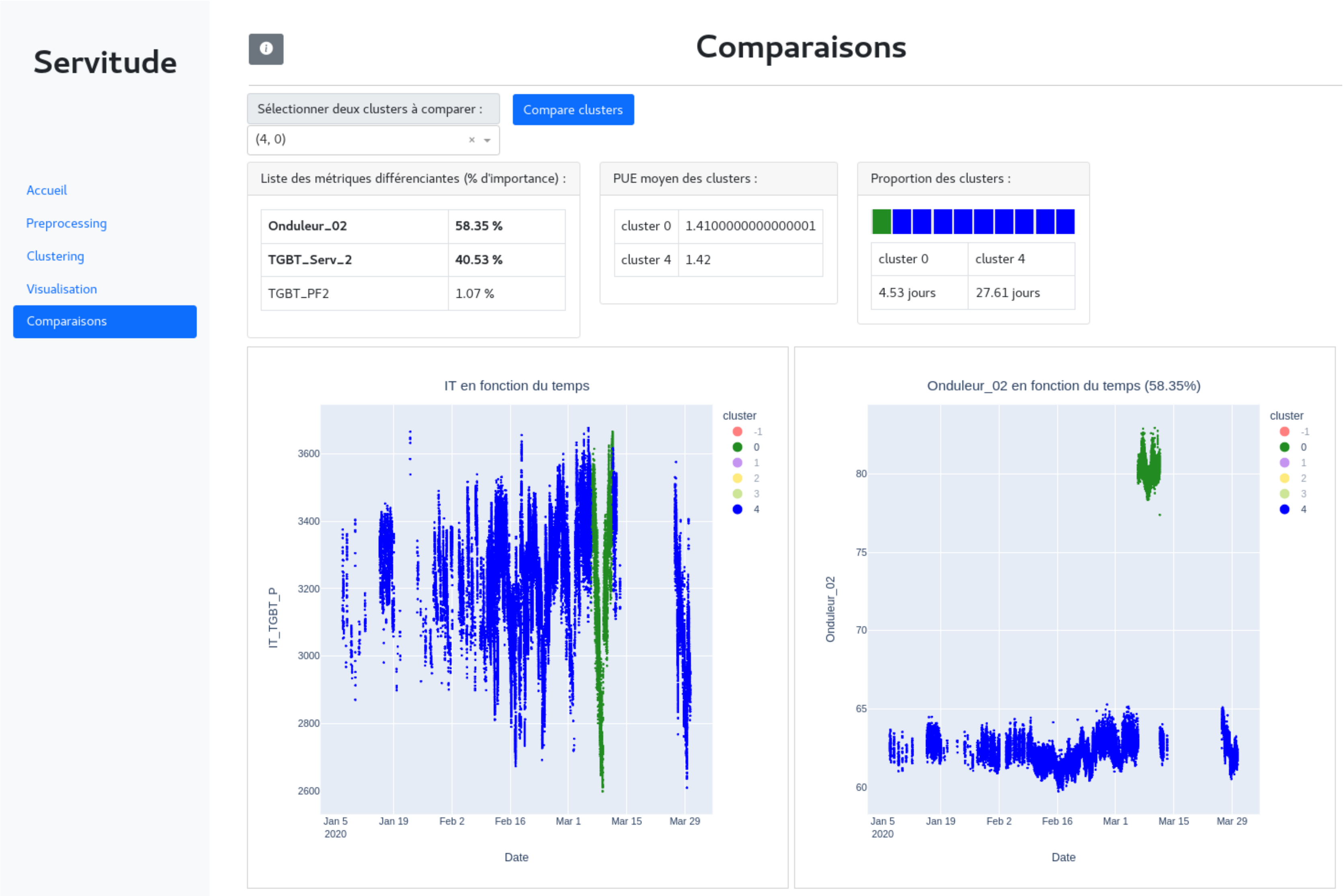


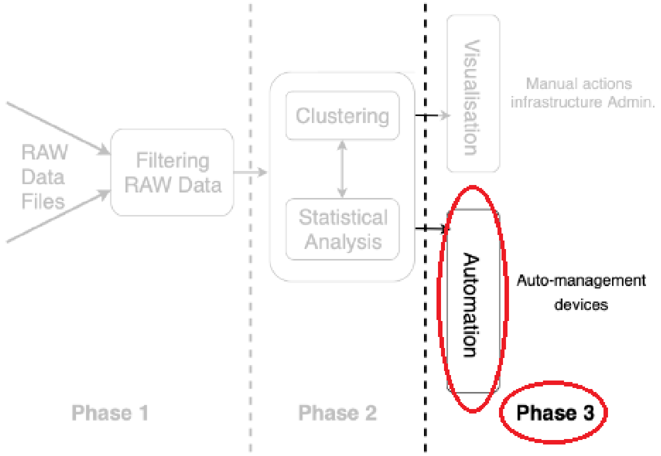
Power (kW) used by an inverter Q1 2020



➢ **Abnormal value for this inverter: an anomaly has been found**

Phase 3: Automation

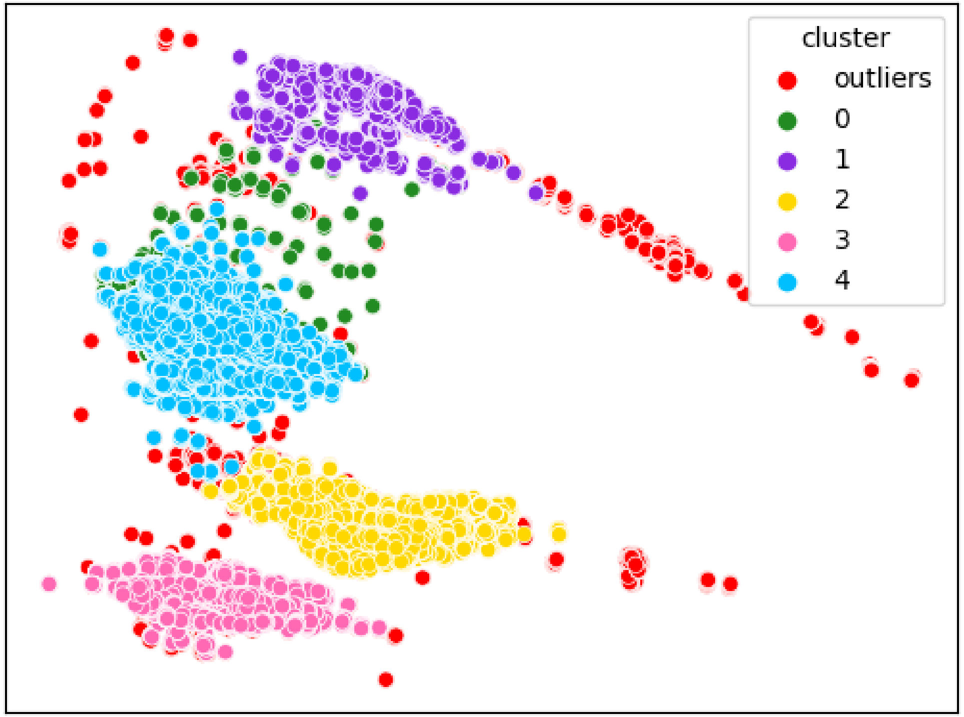




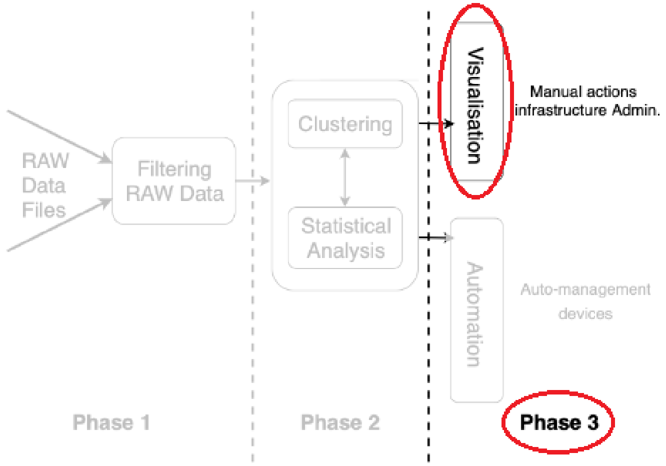
- Based on Dash, an open source library available in Python 3
- Cluster comparisons are done automatically

Phase 3: Visualisation

- t-SNE algorithm (t-distributed Stochastic Neighbor Embedding) used to represent multi-dimensional data in a 2D representation



t-SNE visualisation of the clustered dataset Q1 2020



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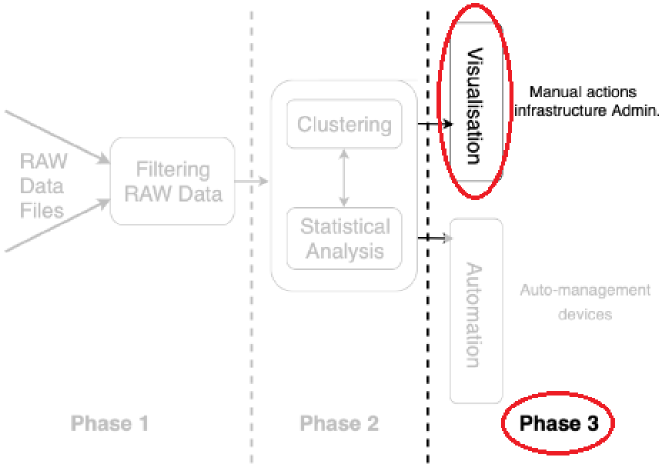

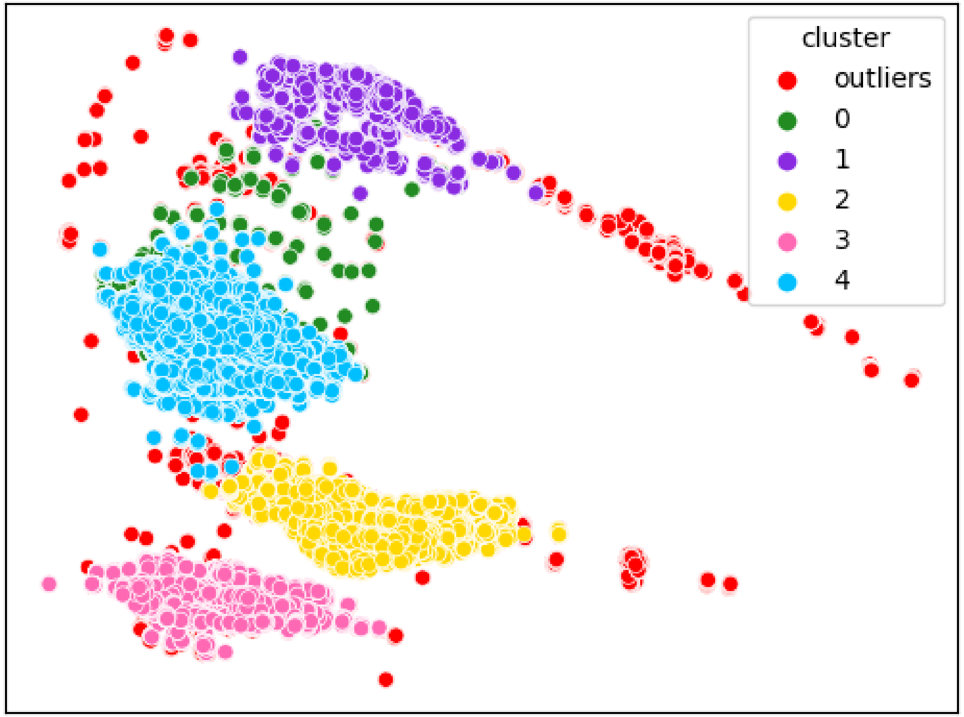

t-SNE visualisation of the clustered dataset Q1 2020

- All these visualisations (time-series, t-SNE, 3D) with or without clustering are available to our administrators in the application

Results and discussion

- Capable of detect anomaly
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  - Look for the most stable and lowest PUE
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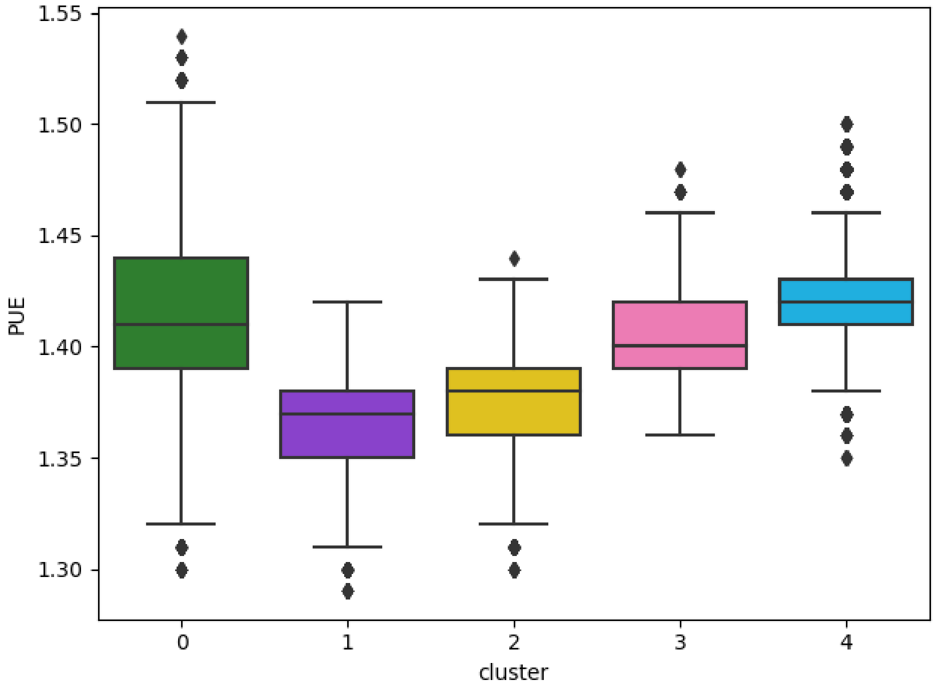

PUE variation Q1 2020

Results and discussion

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- **What's about PUE ?**
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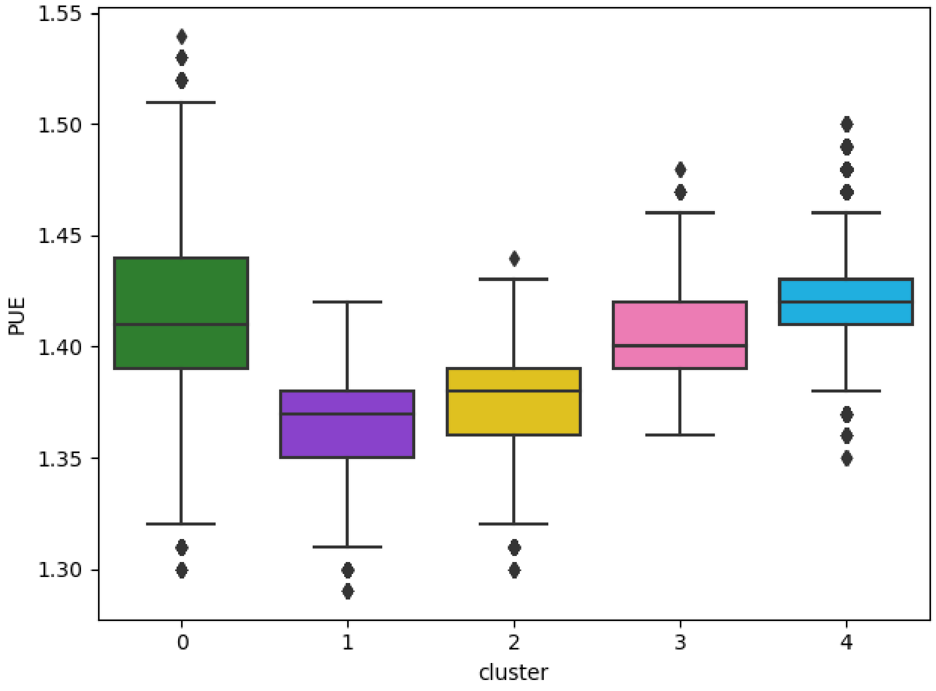
→ A guideline for PUE improvement according to the workload is suggested to the infrastructure admin



PUE variation Q1 2020

Conclusion and future works

- Generic supervision methodology with ML-based algorithms
  - clear and dynamic supervision
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- Tool available for infrastructure admins
  - preparation and clusterisation of data
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Conclusion and future works

- Generic supervision methodology with ML-based algorithms
  - clear and dynamic supervision
  - highlight similar or abnormal behaviours
- Tool available for infrastructure admins
  - preparation and clusterisation of data
  - visualisation of time series, t-SNE, 3D
  - automatic cluster comparisons
- Prospects:
  - implementation of alarms to warn of changes within the same operating mode
  - anticipation of deviant behaviour

Questions?

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