Brunel University London

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Prediction of wastewater N2O emissions using artificial Neural Networks.

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Overview

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- Methodology
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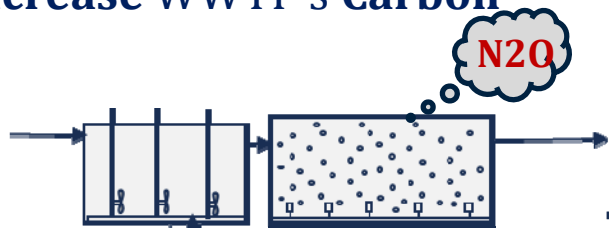
Introduction

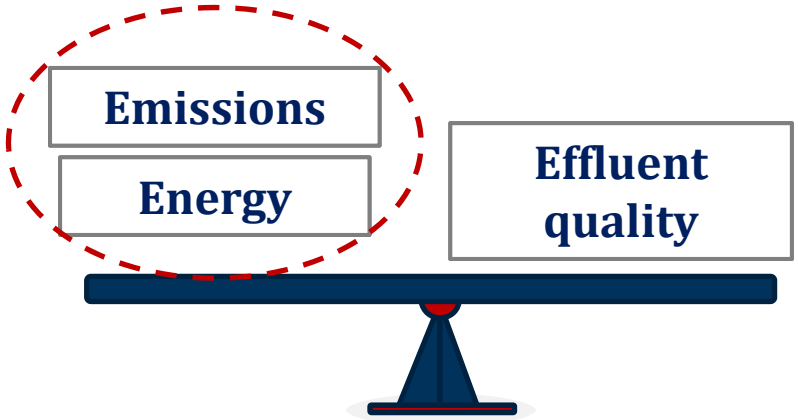
Wastewater treatment **design** and **operation** ➡ **outdated engineering guidelines** from the early 20th century [1]

- **EU 3**% of generated **electricity** ➡ **water industry** [2]
- Solely **N2O** emissions ➡ **60%**[3], or up to **78%**[4] **increase** WWTP's **Carbon Footprint.**



A new sustainable perception of wastewater treatment.

- Need to include GHG emissions/energy consumption in operational strategies ➡ sustainability [5]
- Limited studies [6, 7]



Introduction

Clustering, **artificial neural networks**, **decision trees and classifiers** have been used in WWTPs to:

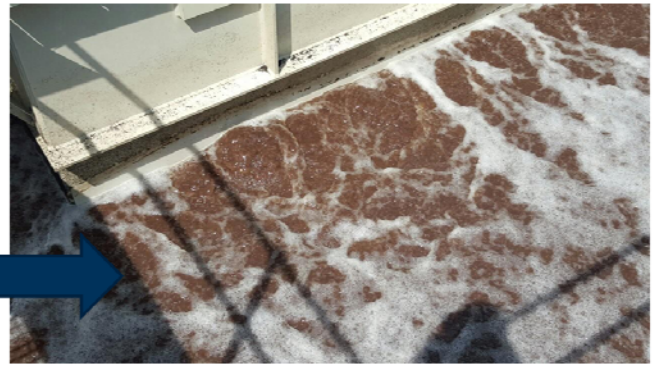
(i) improve process monitoring [8] and provide **insights** [9]

(ii)identify and isolate **process faults** [10] and **sensor faults** [11]

(iii) **predict** significant **operating variables** [12]

However…

- **Few data-driven monitoring** approaches in **full-scale applications**[13]
- **Statistical analysis** is **seldom done** [14]
- **Little guidance** for selection of the **most appropriate** AI **method**[15]



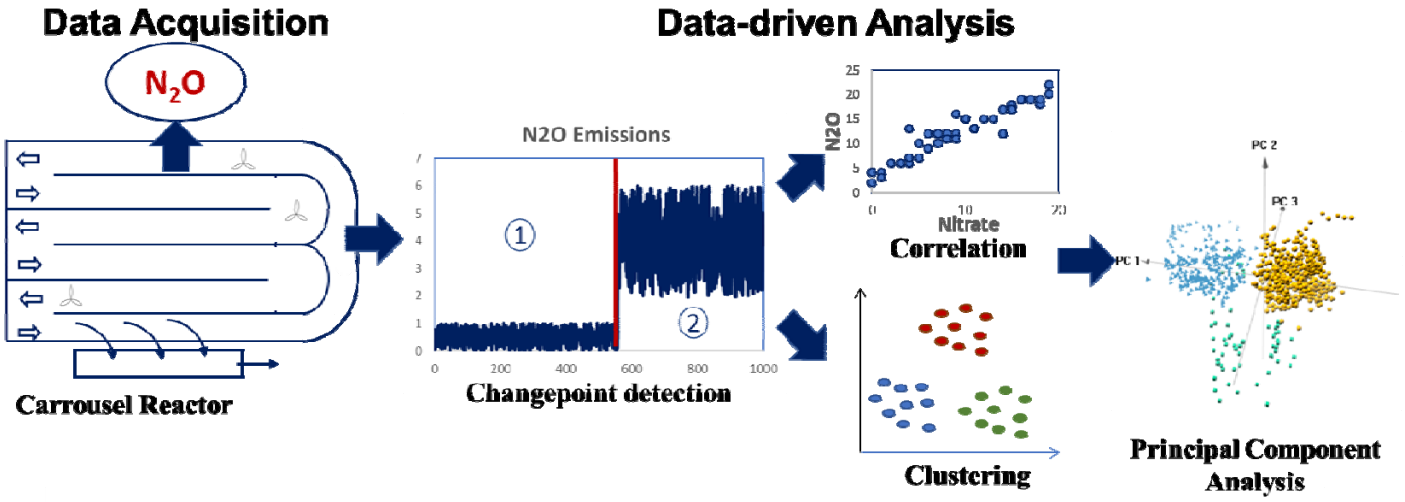
Minworth STW

Aim and objectives

Investigate if **data-driven** methods and **multivariate analysis can** provide **insights** on the **combined effect** of the **operating variables** on **N2O emissions**

WWTP processes are **subject to change**. How can these **changes** be **detected**, and how can they be **considered** in **N2O statistical modelling**?

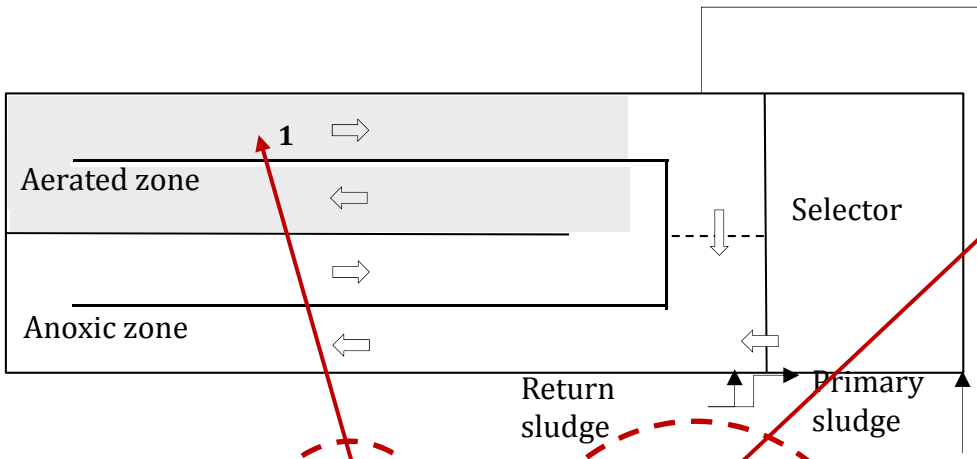
Investigate if **data-driven** methods can be used to predict N2O emissions behavior

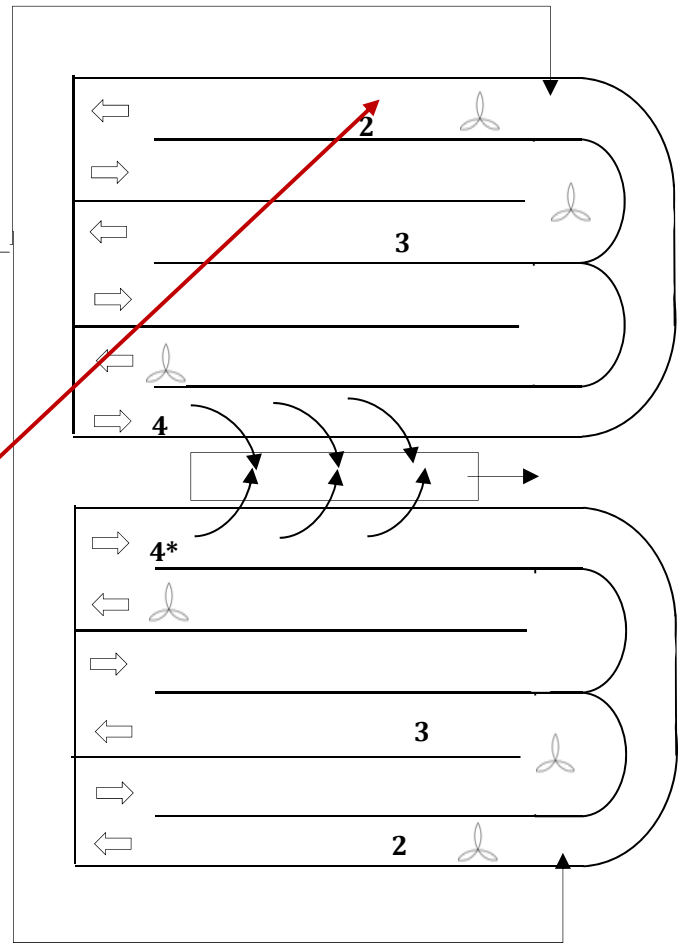


N_2O patterns and dependencies

Methodology

Flow-chart

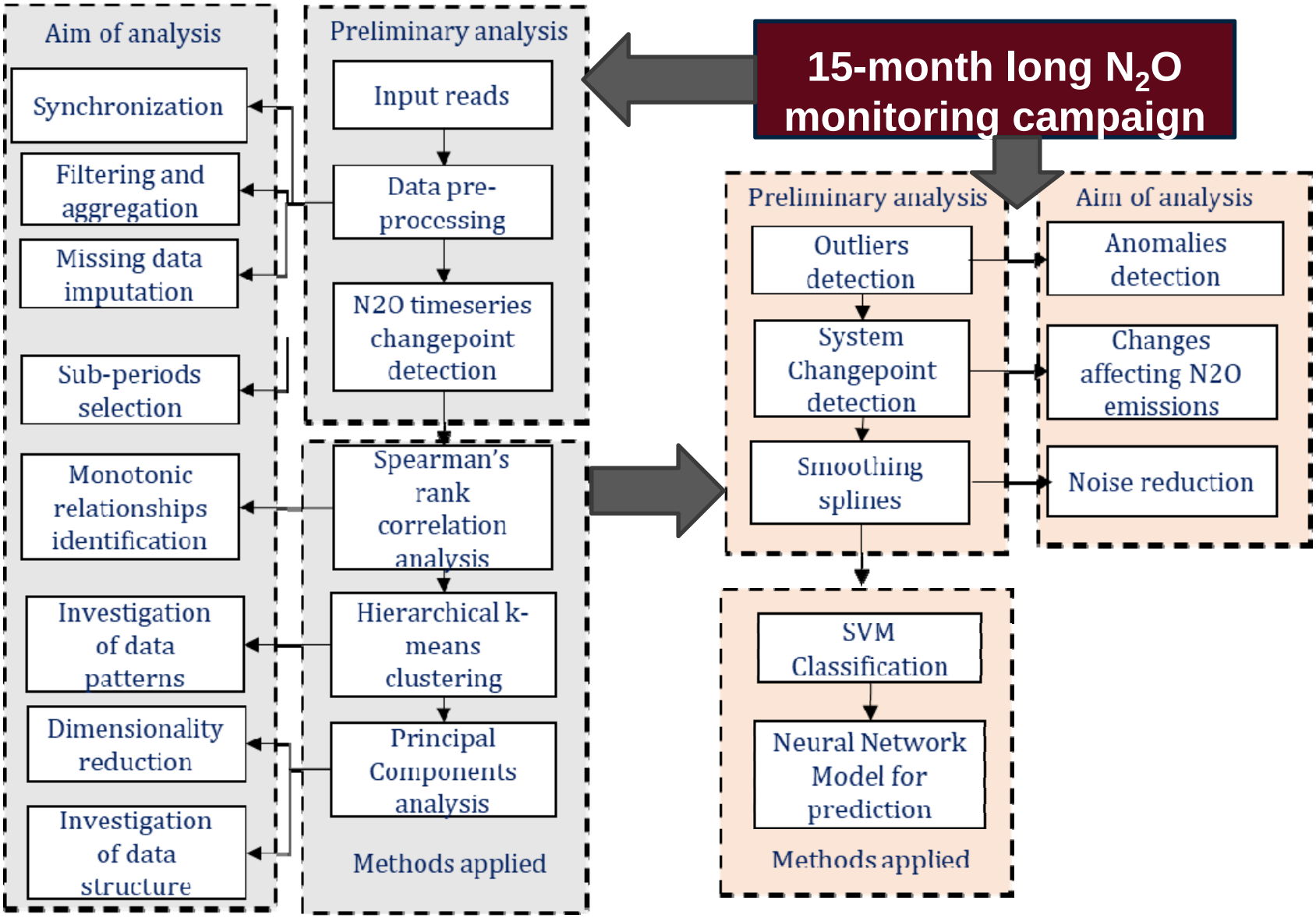




Influent	Plug-flow reactor	Carrousel reactor N
Flow-rate	DO PF	DO1, DO2, DO3
	NH4-N PF	NH4-N C
	NO3-N PF	NO3-N C
	N2O PF	NO2-N C
		N2O C
		Temp C
		TSS C

Kralingseveer WWTP

Methodology

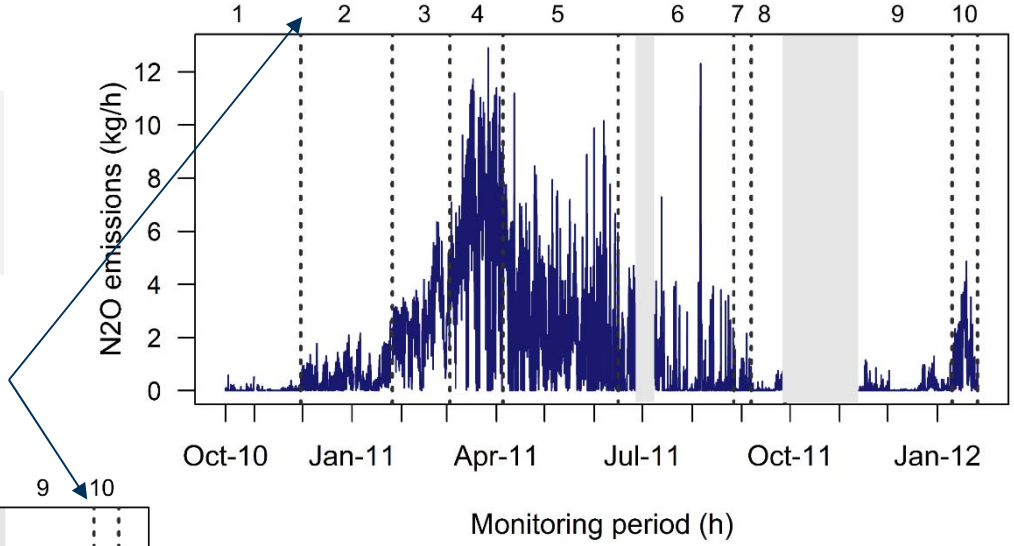


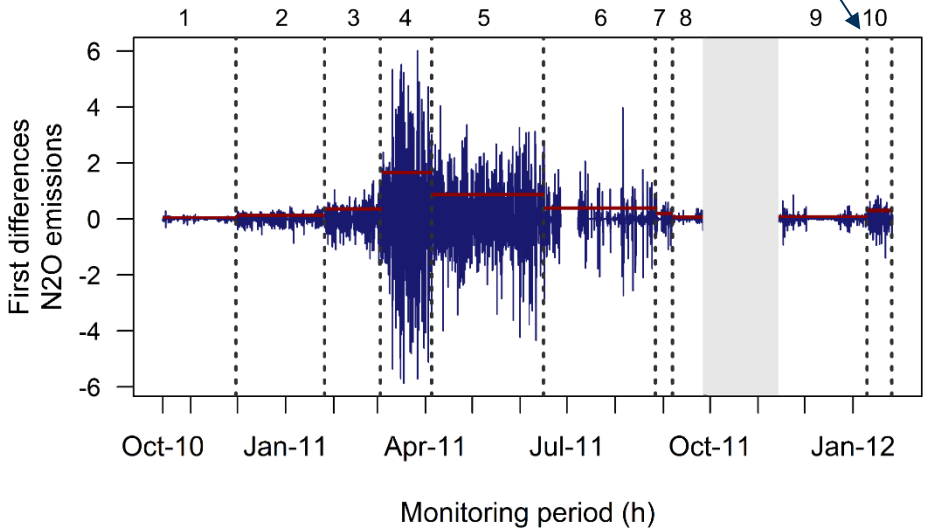
Results

❖Binary segmentation[16] ➡ 10 sub-periods with different N2O emissions profiles

N2O emissions profile in the Northern Carrousel reactor

different sub-periods

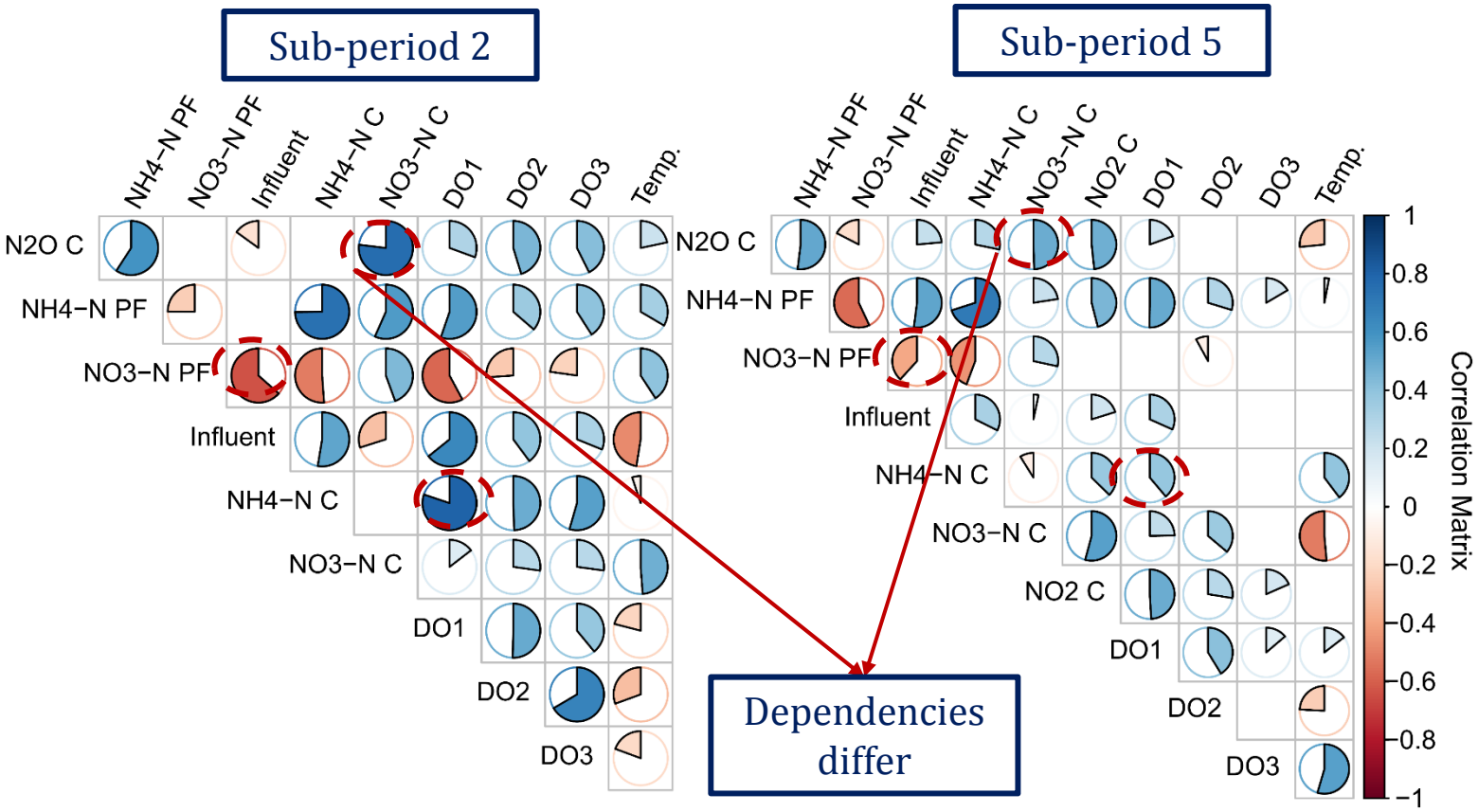




First difference of the N2O emissions timeseries showing the sub-periods

Results

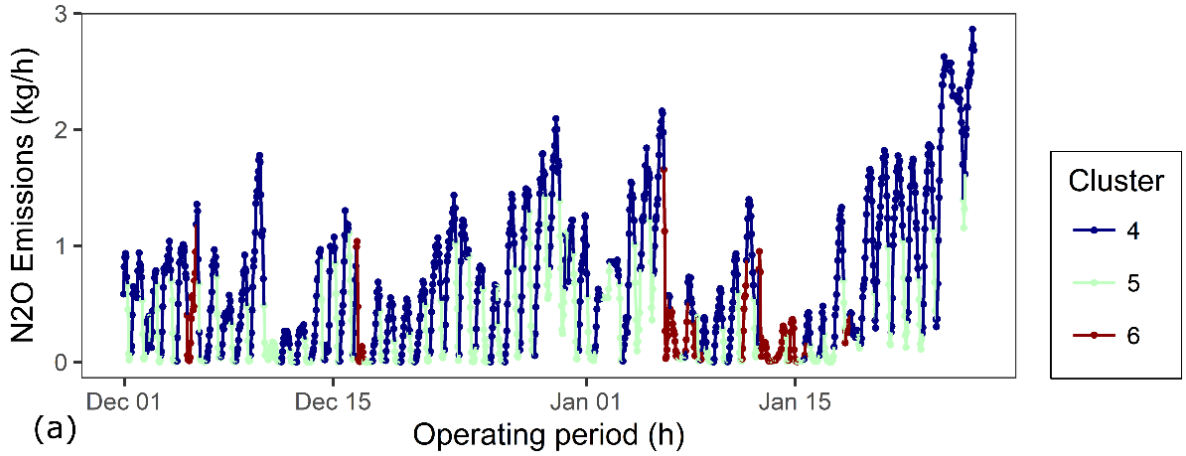
- Spearman's rank correlation [17]
  - Fluctuation between sub-periods
  - N2O correlated with ammonium, nitrate and nitrite
  - Low correlation coefficients can indicate non-monotonic interrelationships



Results

- Hierarchical k-means clustering [18]
  - Reoccurring patterns and their effect on N2O emissions
  - N_2O emission peaks linked with the diurnal behaviour and precipitation events
  - Clusters with NO3-N plug-flow <1 mg/L and Carrousel reactor <4 mg/L
    → N2O fluxes >2 kg/h

N_2O emissions profile



P	Cl	N_2O C	NH_4-N PF	NO_3-N PF	Influent	NH_4-N C	NO_3-N C
		kg/h	mg/l	mg/l	m^3/h	mg/l	mg/l
2	4	0.87	**15.30**	2.05	3827	1.51	8.61
	5	0.21	**9.13**	3.69	3419	0.74	5.28
	6	0.24	12.51	0.81	**11132**	4.52	5.42

Hierarchical k-means clustering results

Results

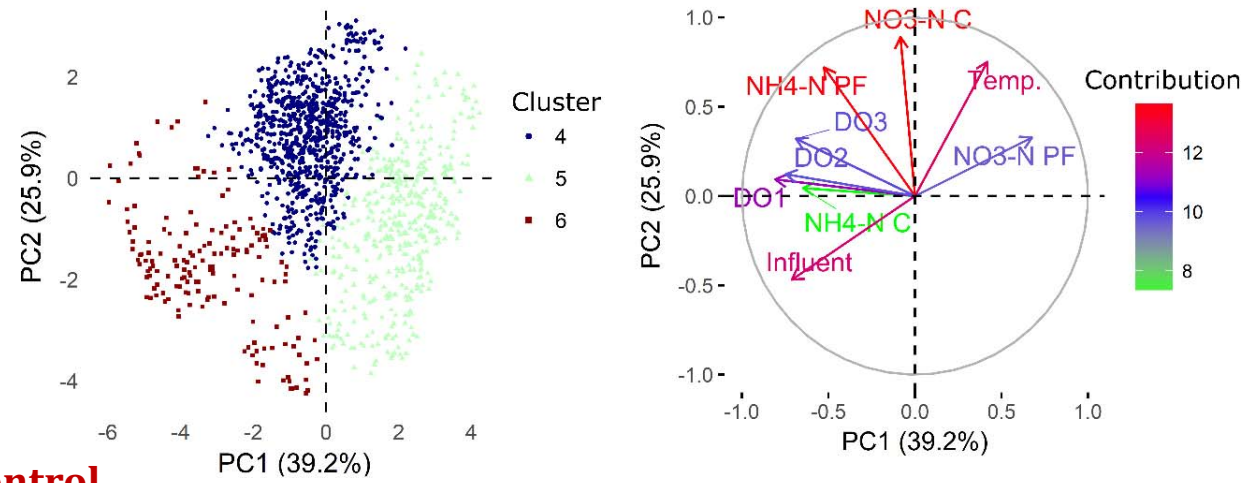
- Principal component analysis[19]
  - Validated the findings from the clustering analysis
  - Ammonium, nitrate, nitrite, influent flow-rate and temperature, explained more than 65% of the variance in the system for the majority of the sub-periods.

PC Loadings

PC2 and N_2O correlation emissions equal to 0.72

Variable	PC1	PC2
NH_4-N PF	-0.28	**0.47**
NO_3-N PF	**0.36**	0.21
Influent	**-0.38**	**-0.31**
NH_4-N C	**-0.34**	0.03
NO_3-N C	-0.04	**0.58**
DO1	**-0.43**	0.06
DO2	**-0.40**	0.08
DO3	**-0.37**	0.21

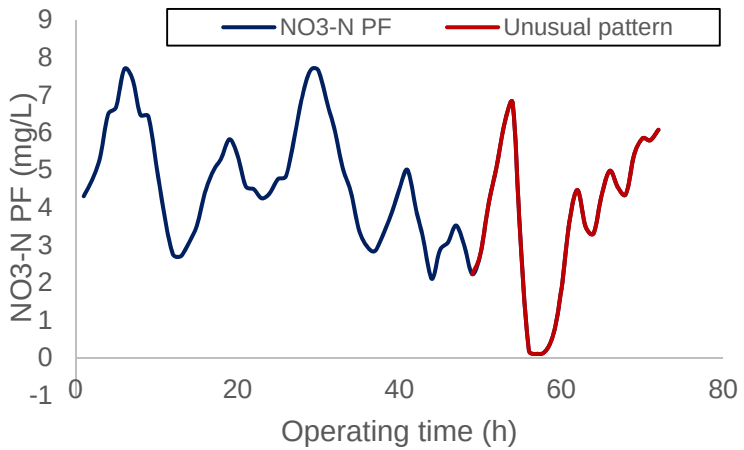
control strategy of the reactor.

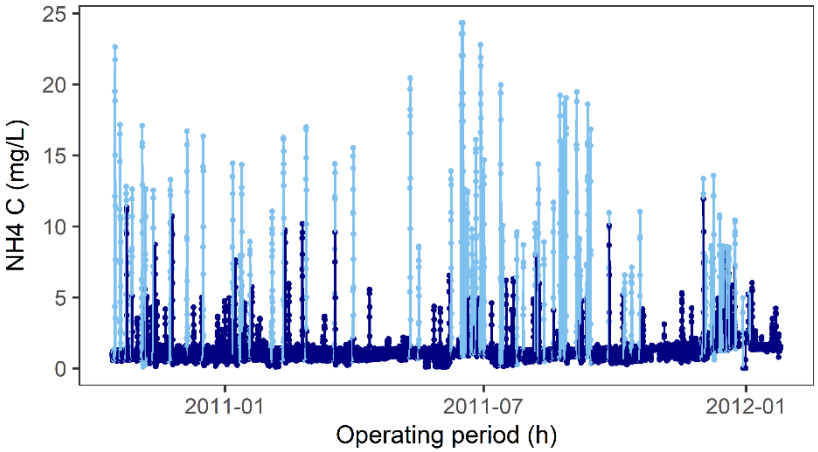


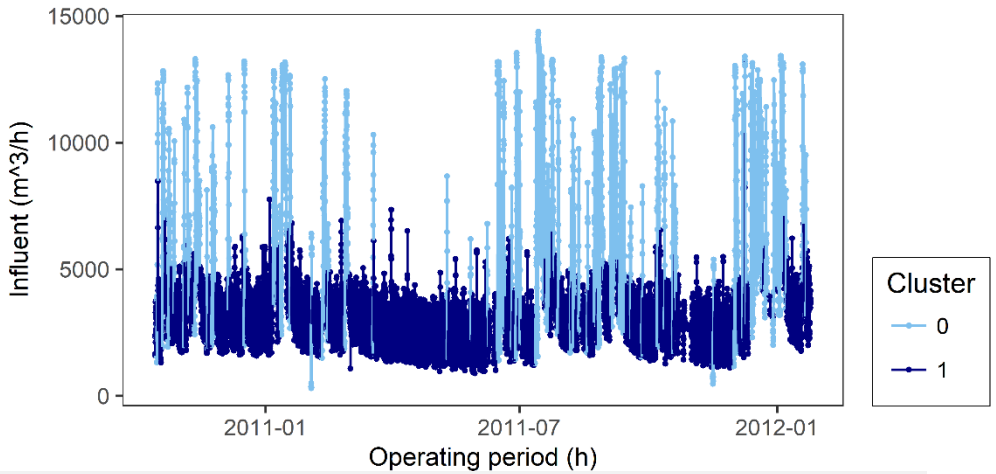
PCA biplot and correlation diagram

Results

- Anomalies detection – DBSCAN clustering [20]
  Identify unexpected patterns in the diurnal profile of the parameters





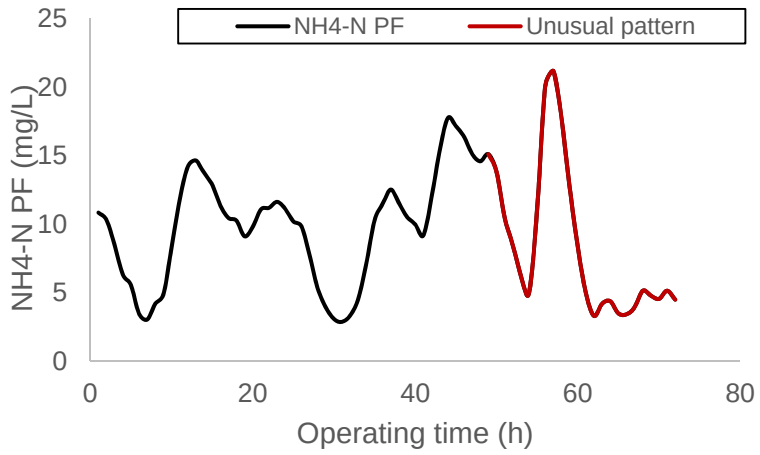


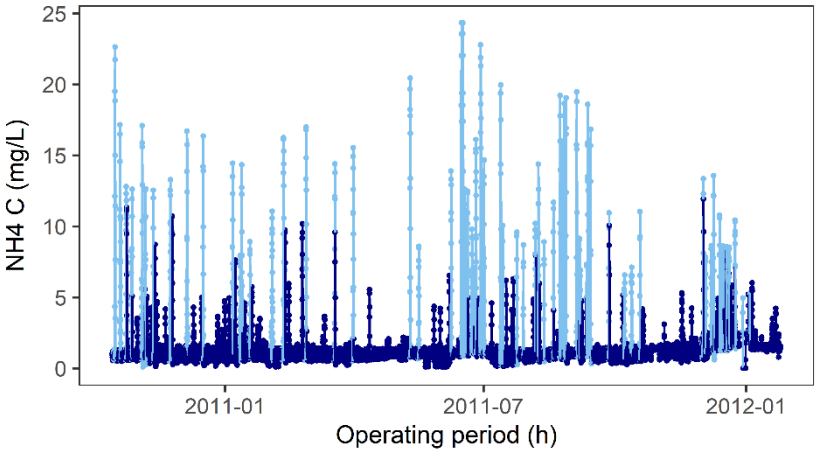
87% common anomalies detected between **NH4-N C** and **Influent** flow-rate

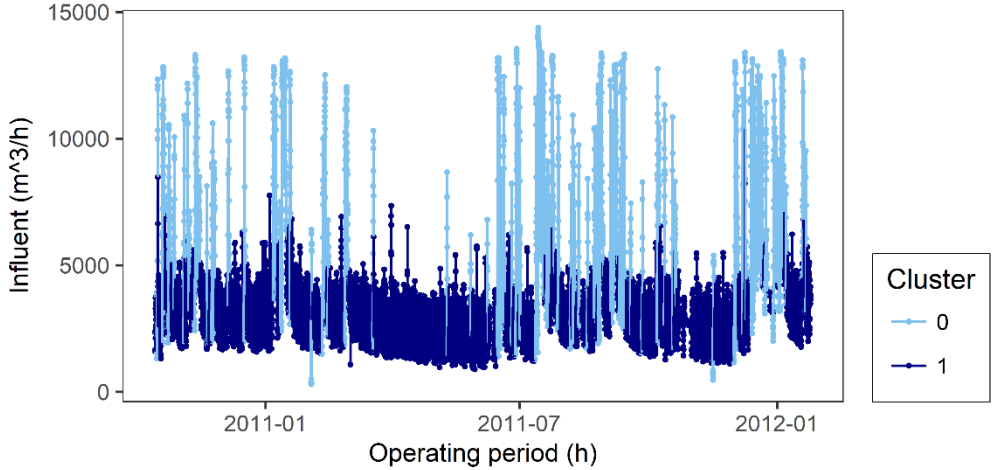
Results

- Anomalies detection – DBSCAN clustering [20]
  Identify unexpected patterns in the diurnal profile of the parameters

  ~80% Common outliers







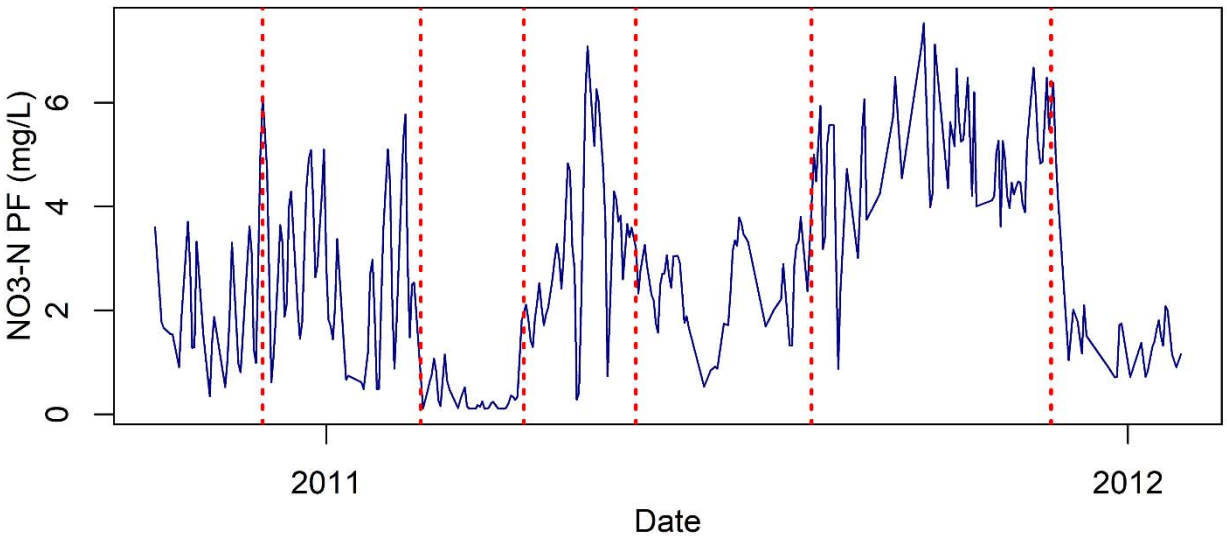
87% common anomalies detected between **NH4-N C** and **Influent** flow-rate

Results

- Sub-period division – NO_3-N PF Changepoint detection

  E-divisive: hierarchical divisive estimation of multiple change points [21]

  Bisection algorithm based on the measurement of divergence between two dataset distributions (nonparametric method).



Cl	1	2	3	4	5	6	7
Mean	1.9	**2.8**	0.4	3.1	2.5	5	1.6
Sd	1.6	**2**	0.6	1.9	1.3	2.4	1.3
Median	1.6	**2.7**	0.3	3	2.7	5	1.4

- Sub-period division – NO_3-N PF Changepoint detection

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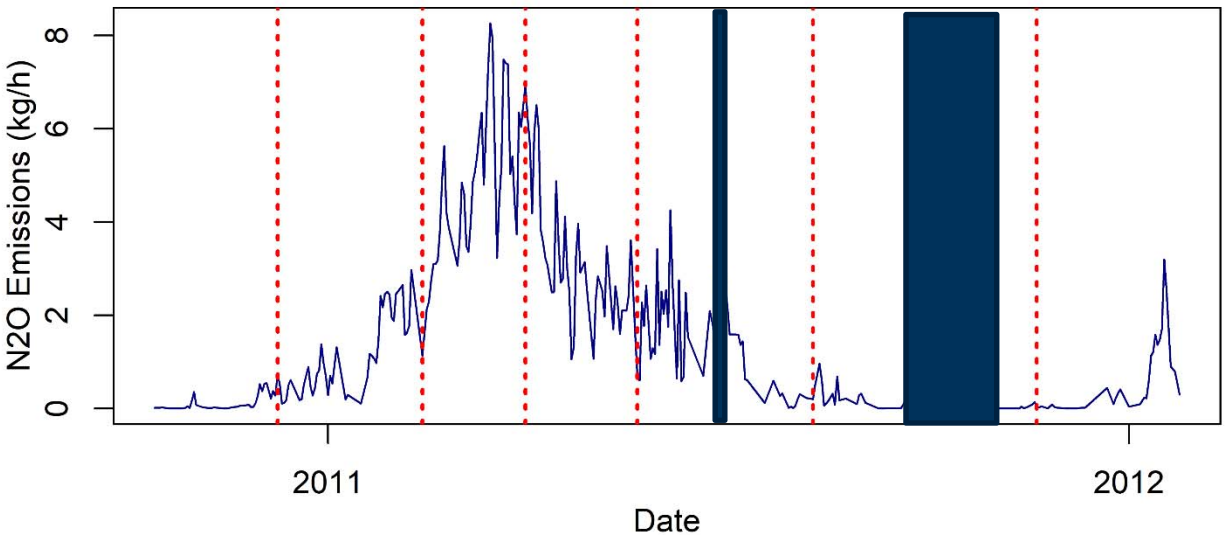
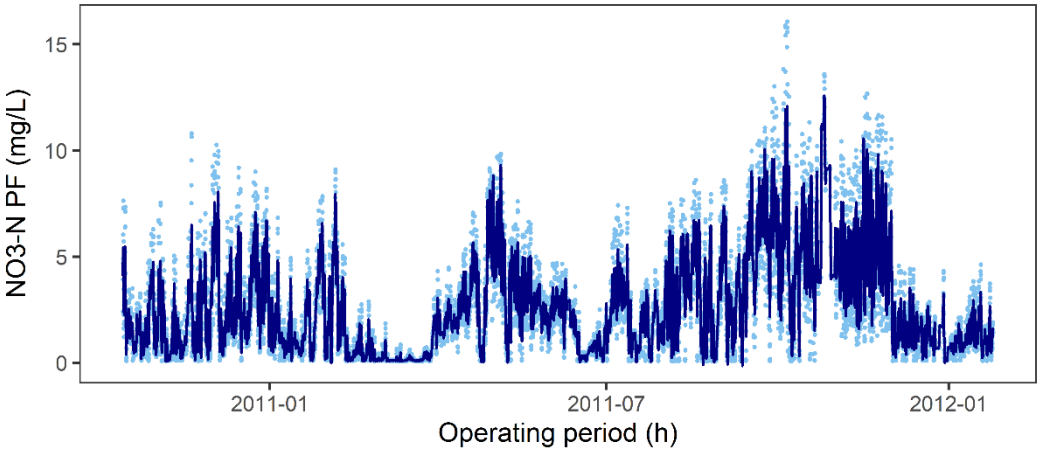


N2O emissions profile sub-periods division

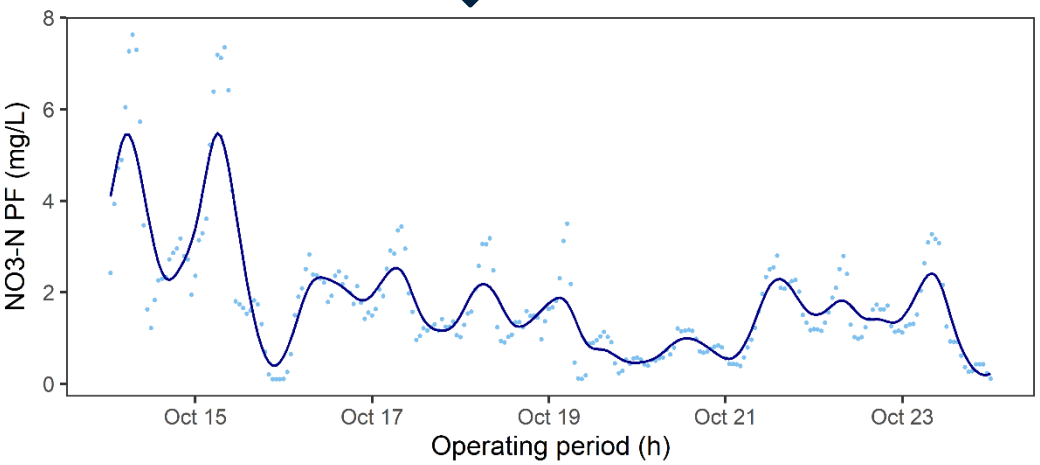
Methodology – Data preprocessing

- Noise reduction – Smoothing splines [22]



The bandwidth of the filtering is as a function of time

Example of NO3-N PF smoothed timeseries



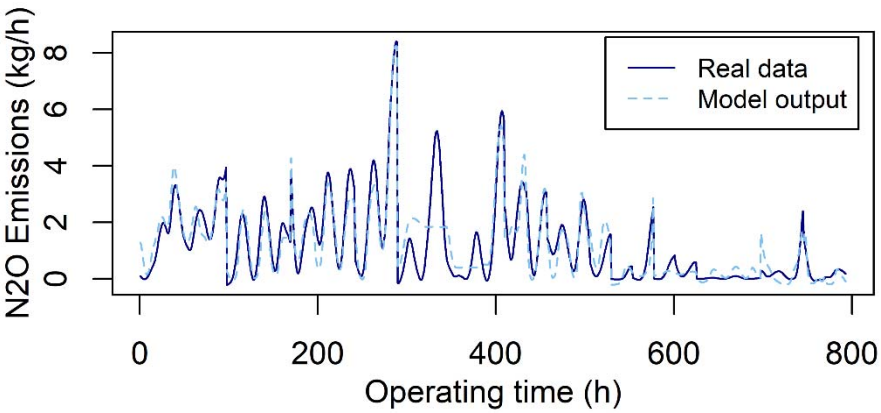
- Data normalization min-max

Results

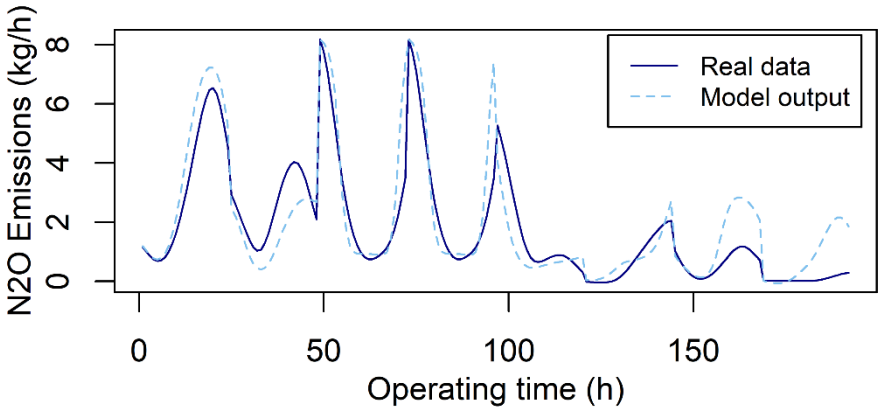
❖ Support Vector machine classification [23]

Method	Data-base	% wrong period
Method 1	SVM Train	0.6%
	SVM Test	5%

❖ Neural Network models [24]



NN model sub-period 5, Train



NN model sub-period 5, Test

Conclusions

- A combination of changepoint detection algorithm, hierarchical k-means clustering and principal component analysis was used to:
  - Detect and visualize disturbances in the system
  - Detect ranges of operating variables that have historically resulted in low or high ranges of N2O emissions
  - Can be used to assist researchers and operators to understand and control the emissions using long term historical data.
- Spearman's rank correlation analysis:
  - showed significant univariate correlations between N2O emissions and ammonium, nitrate and nitrite concentrations.
  - The correlation coefficients fluctuated between the 10 sub-periods.
  - Low values for the correlation coefficients indicated non-monotonic interrelationships that Spearman's rank correlation cannot identify.
- Hierarchical k-means clustering:
  - Provided information on the existence of reoccurring patterns and their effect on N2O emissions.
  - N2O emission peaks were linked with the diurnal behavior of the nutrients' concentrations, with rain events and low nitrate concentrations in the preceding plug flow reactor

Conclusions

- Principal component analysis:
  - validated the findings from the clustering analysis and showed that ammonium, nitrate, nitrite, influent flow-rate and temperature, explained more than 65% of the variance in the system for the majority of the sub-periods.
  - The first principal component corresponded to the control strategy of the reactor.
- DBSCAN :
  - Isolated unusual patterns in the parameters
  - Confirmed that Precipitation events are linked with high NH4-N concentration in the Carrousel effluent
- SVM classification and neural network model:
  - SVM test data classification error ranged between 3-10%.
  - NN model could predict the profile of N2O emissions for sub-periods 1, 2, 3, 4, 5 and 7

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Acknowledgements

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Thank you for your attention!