Développement d’un système de prototype intelligent pour le contrôle et l’optimisation de traitement des eaux usées

Marcello Serrao

ÉCOLE DOCTORALE UNIVERSITÉ PARIS-EST
Sciences, Ingénierie et Environnement

UNIVERSITÉ LAVAL

leesu
laboratoire eau environnement systemes urbains

SIAAP
Service public de l’assainissement francilien

WSMART

Café Sciences LEESU – 29 janvier 2021

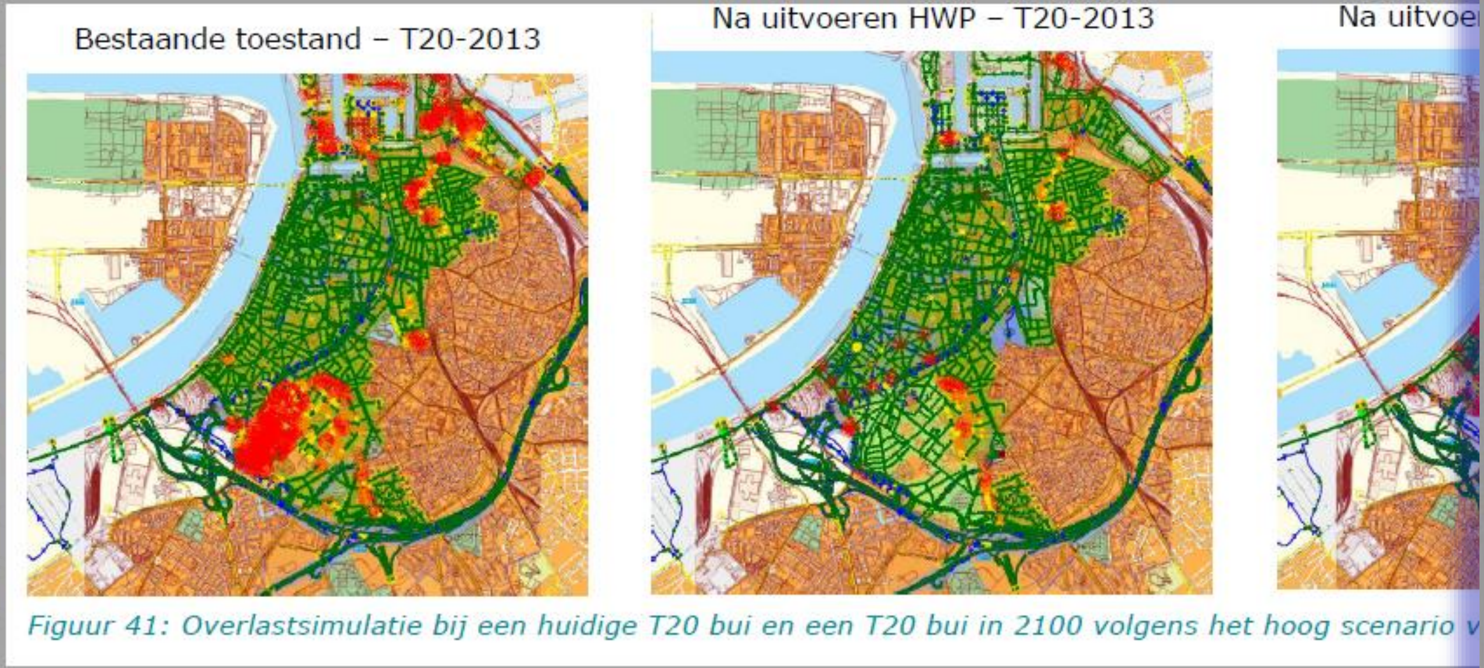
MOCOPÉE
Soutenu par le Service Public de l’Assainissement Francilien (SIAAP)

L’ordre du jour

- Qui suis-je ? – 5’
- Cadre de mon projet de recherche – 10’
  - Le contexte
  - Les objectifs
  - Les partenaires
  - La valeur ajoutée
- Méthodologie – 10’
  - La modélisation, qualité de données, algorithmes d’IA
  - Plan du travail
  - Site pilot
- Les premiers résultats – 5’
- Contributions académique – 5’

Marcello Serrao – Candidat Doctorant

- Master en géographie physique – spécialisation hydrologie (1999) - l’université d’Amsterdam
- Bachelor en études environnementales (2004) - l’Open Université Pays-Bas
- Candidate doctorant à LEESU depuis mars 2020.


Bestaande toestand – T20-2013

Na uitvoeren HWP – T20-2013

Na uitvoe

Figuur 41: Overlastsimulatie bij een huidige T20 bui en een T20 bui in 2100 volgens het hoog scenario v


6 CLEAN WATER AND SANITATION

Progress on Transboundary Water Cooperation

Global baseline for SDG indicator 6.5.2

2018

UN WATER

UNECE

Expéri
- 201
- 201
- 201
- 200

Mes c
- Bo
- Bo s
  pré
- Je ville
  plu

Je suis né et ai grandi à Amsterdam
Bilingue Anglais et Néerlandais
Je suis marié, nous avons 3 enfants et habitons en région parisienne depuis 2017

Digital Water Revolution

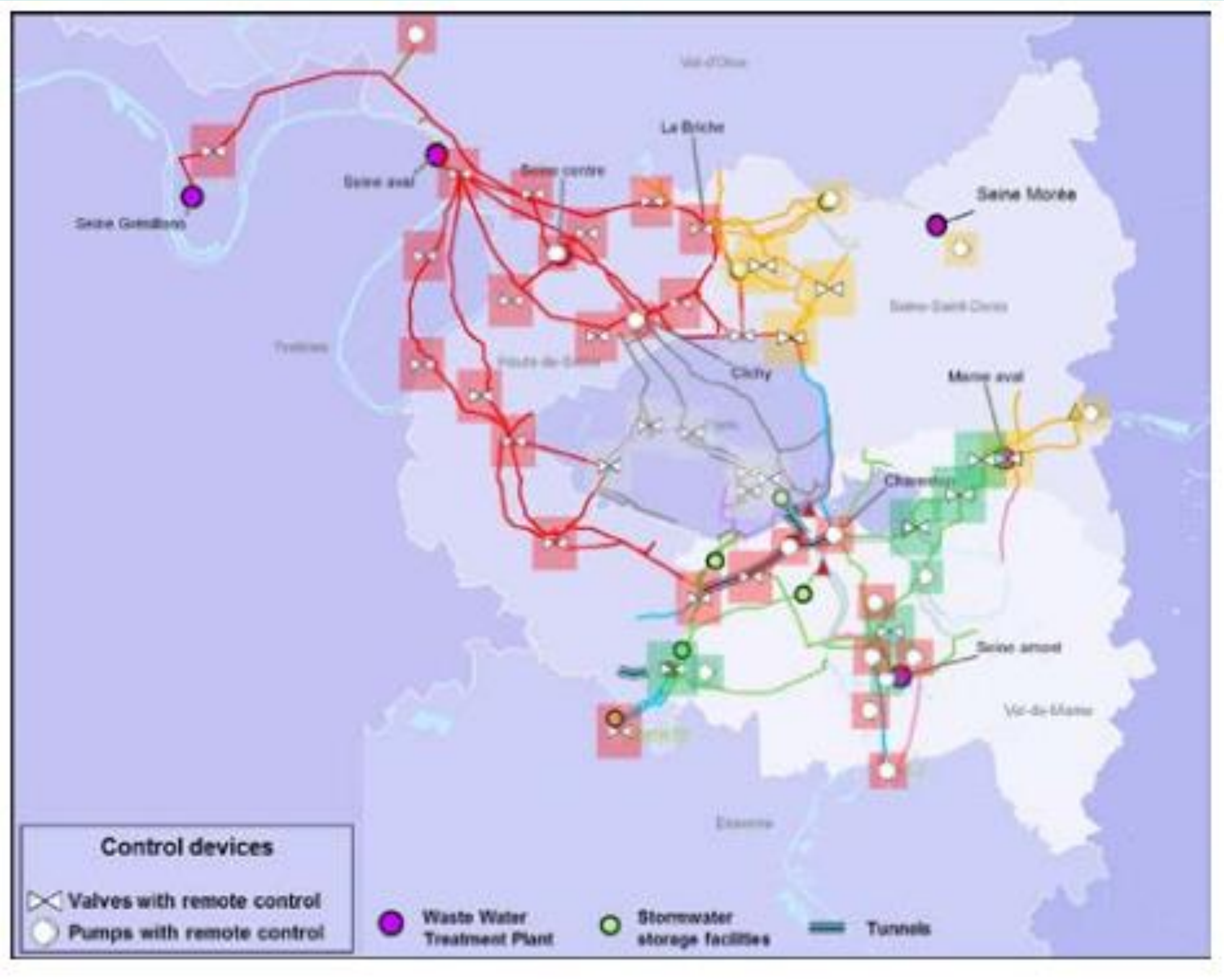
- Digitalisation of process monitoring and control in many industries, but…

- Wastewater Treatment is
  - Physical, biological, chemical processes > complex interactions
  - High variable conditions and operating parameters > harsh conditions
  - Large investement costs with long life-span of installations > aging infrastructure
  - Evolution of stricter effluent discharges & transformation to wastewater recycling, nutrient and energy recovery

- State-of-the-Art
  - Introduction of ICT and SCADA systems – since 1970’s
  - Development of online reliable sensors for quantity (1990’s) and main quality indicators – since 2000’s
  - Introduction of sensor based process control PID controllers, FeedForward & FeedBack control;
  - Development of simulation models based on process understanding (‘white box models’)
  - Introduction of application programming interfaces (APIs) to retrieve and share data from mutiple platforms

Smart Design + Smart Use + Smart Control = Model-Supported Operations

Challenges for Digital Wastewater Revolution



Smart Digital Control of Wastewater Flow through Transport Network :

- Reduce combined sewer overflows of untreated wastewater
- Predictive maintenance to reduce obstruction / failures of critical points

Future development =

Model-supported operation & smart Digital Control of Processes at the Wastewater Treatment Plant

Research objectives and framework

- **Objective I: integrated simulation process model**
- (Re-)**calibration** and **validation** of a deterministic model integrating Chemically Enhanced Settler, Biofilter, Membrane Bio Reactor
- Simulate and evaluate the effects of different scenarios and create data bank
- **Objective II: smart control system**
- Apply artificial intelligence algorithmes (machine learning) for data analysis and data quality control
- **Objective III: hybrid adaptive digital twin**
- Integration of data-based model for analysis (‘black box model’) with knowledge-based process model (‘white box’)

Partenaire	Rôle	Répartition du temps de travail

Comité de thèse

- LEESU : professeur Bruno Tassin (directeur de la thèse)
- Model*eau :* professeur Peter Vanrolleghem (codirection)
- SIAAP : Dr. Jean Bernier et Dr. Vincent Rocher
- W-SMART : professeur Ilan Juran

Duration : March 2020 – March 2023

L’apport de ma thèse

- Better control a
- Modelling is go … erations:
  1. Calibratio … s
  2. Determini … ‘slow’
  3. Changes
- My thesis aims … inously:
  - Perform d
  - Generate
  - Calculate

… is

… nding on pollutant

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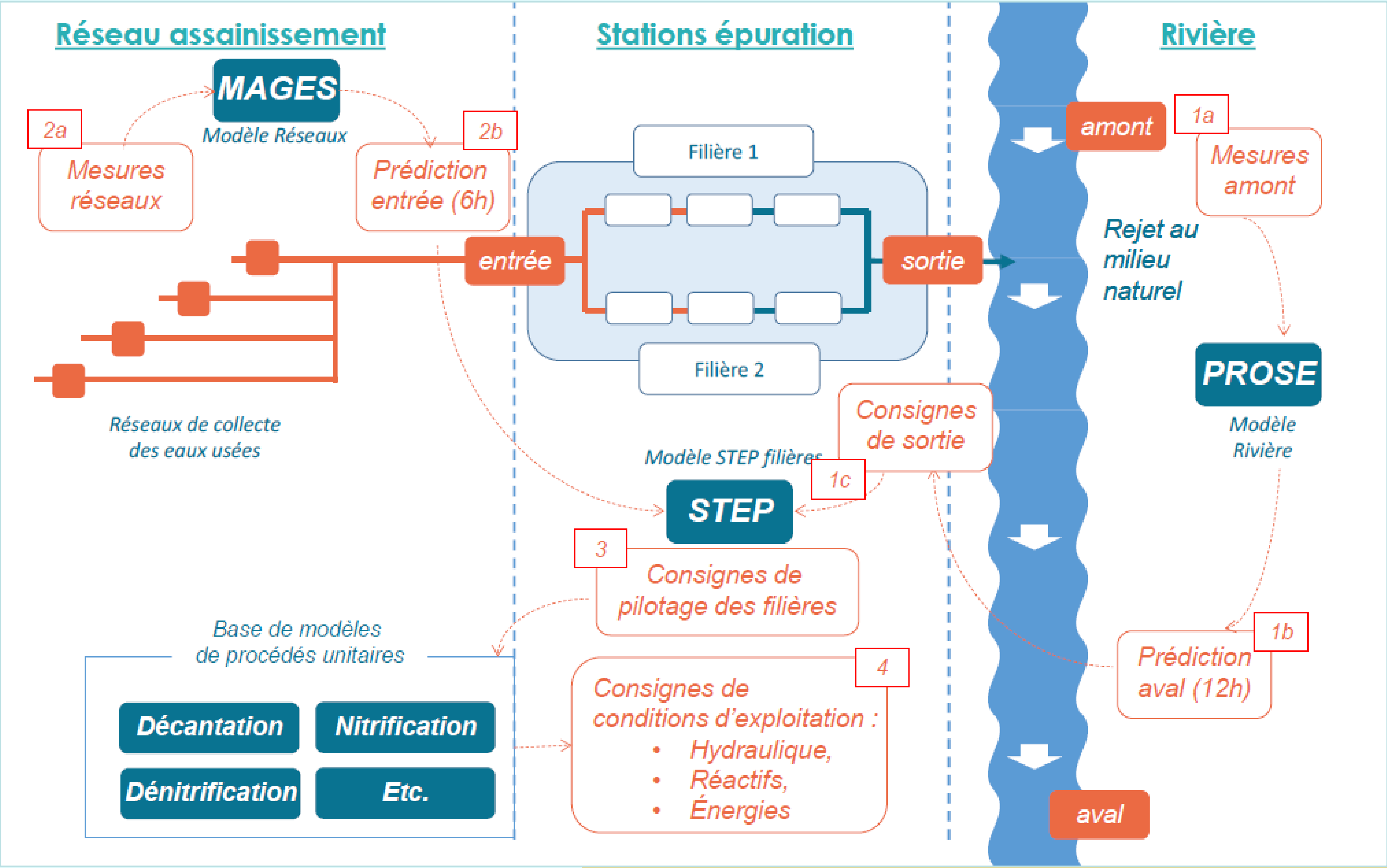
Model-s



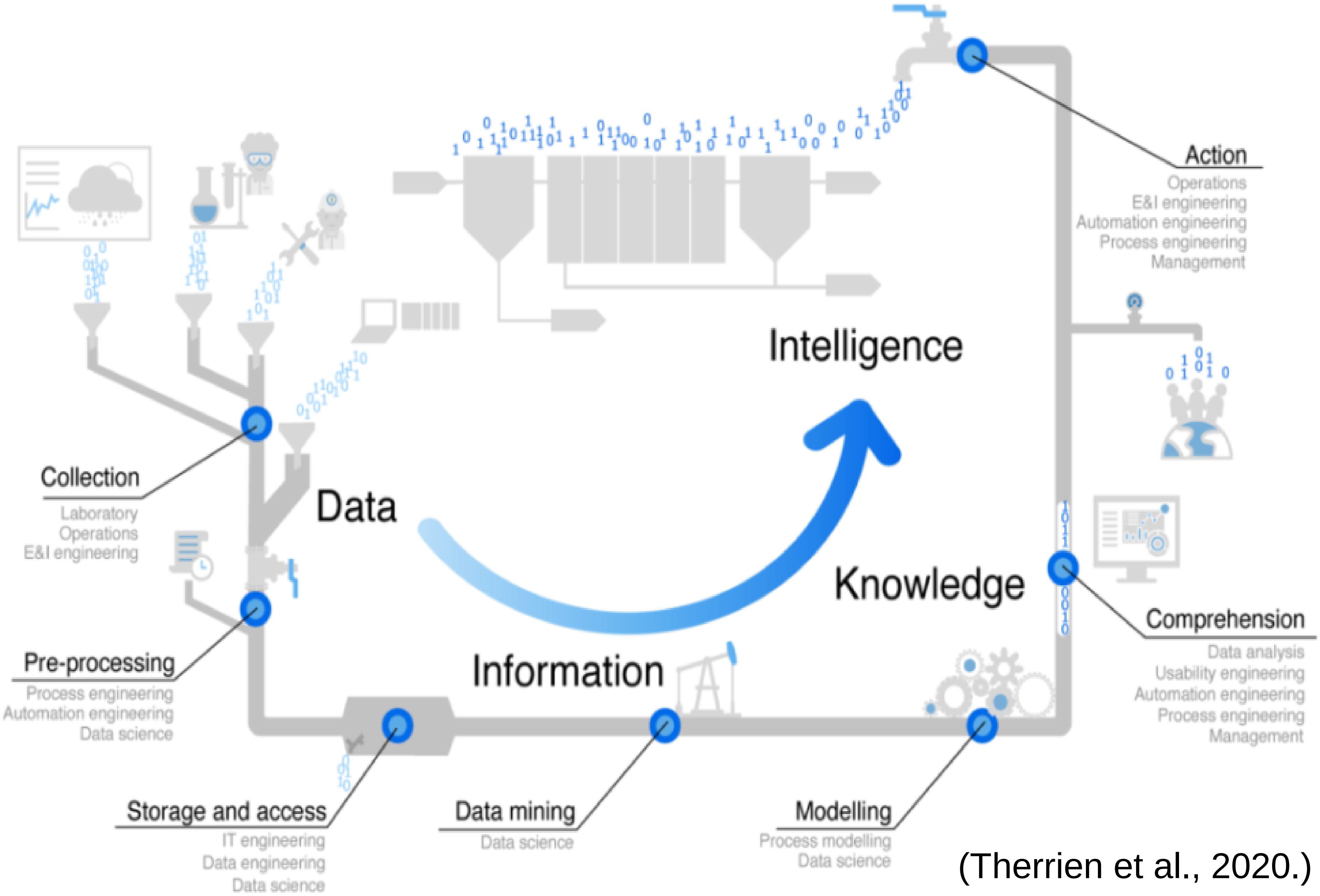
- Long term : central component of an Integrated Urban Water System : River + WWTP + Transport Network

La Méthodologie

- Online Data Quality Analysis
- Process Modelling
- Data Management by Machine Learning

Digital Twin will:

- Follow key process indicators
- Calculate optimization based on real-time data and historical performance
- Detect anomalies
- Alert and give early-warning



(Therrien et al., 2020.)

Méthodologie de la modélisation

Good Modelling Practice (IWA):

Step 1. Project Definition

Step 2. Data Collection and Reconciliation

Step 3. Plant Model Set-up :

- *Use model developped by Jialu Zhu for CEPT and biofiltration;*
- *Apply Fractionation with Interpolation to fill data gaps and create Influent File*
- *Functional check & set parameters values*

Step 4. Calibration and Validation

- *Iterative adjustments of model parameters to fit calculated variables with observed variables at effluent*
- *Methodology described by Mannina et al. 2011:*
  - *1) parameter sub-set selection*
  - *2) model calibration*

Step 5. Simulation and Result Interpretation

- *Run dynamic simulations*
- *Descriptive Statistical Analysis of results to report on Accuracy*

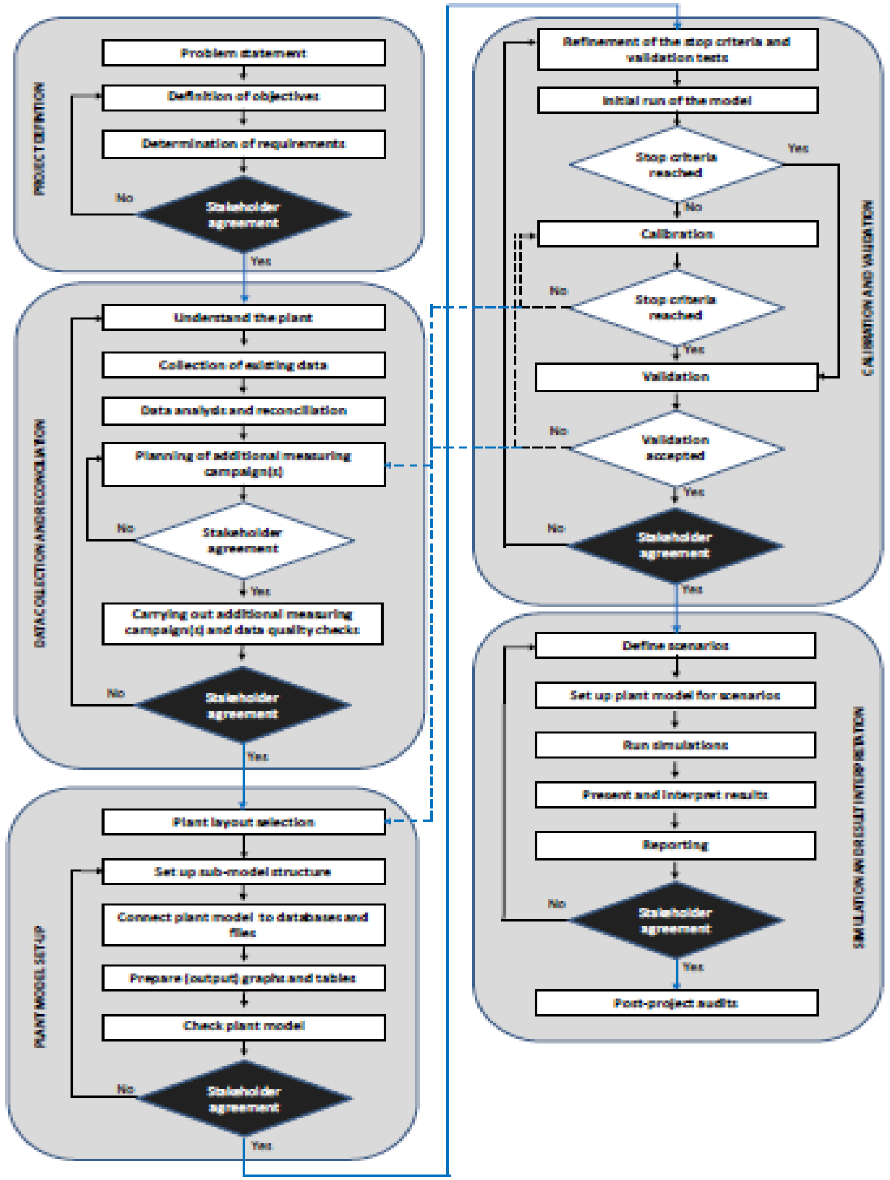


Figure 4-1: The proposed GMP Unified Protocol

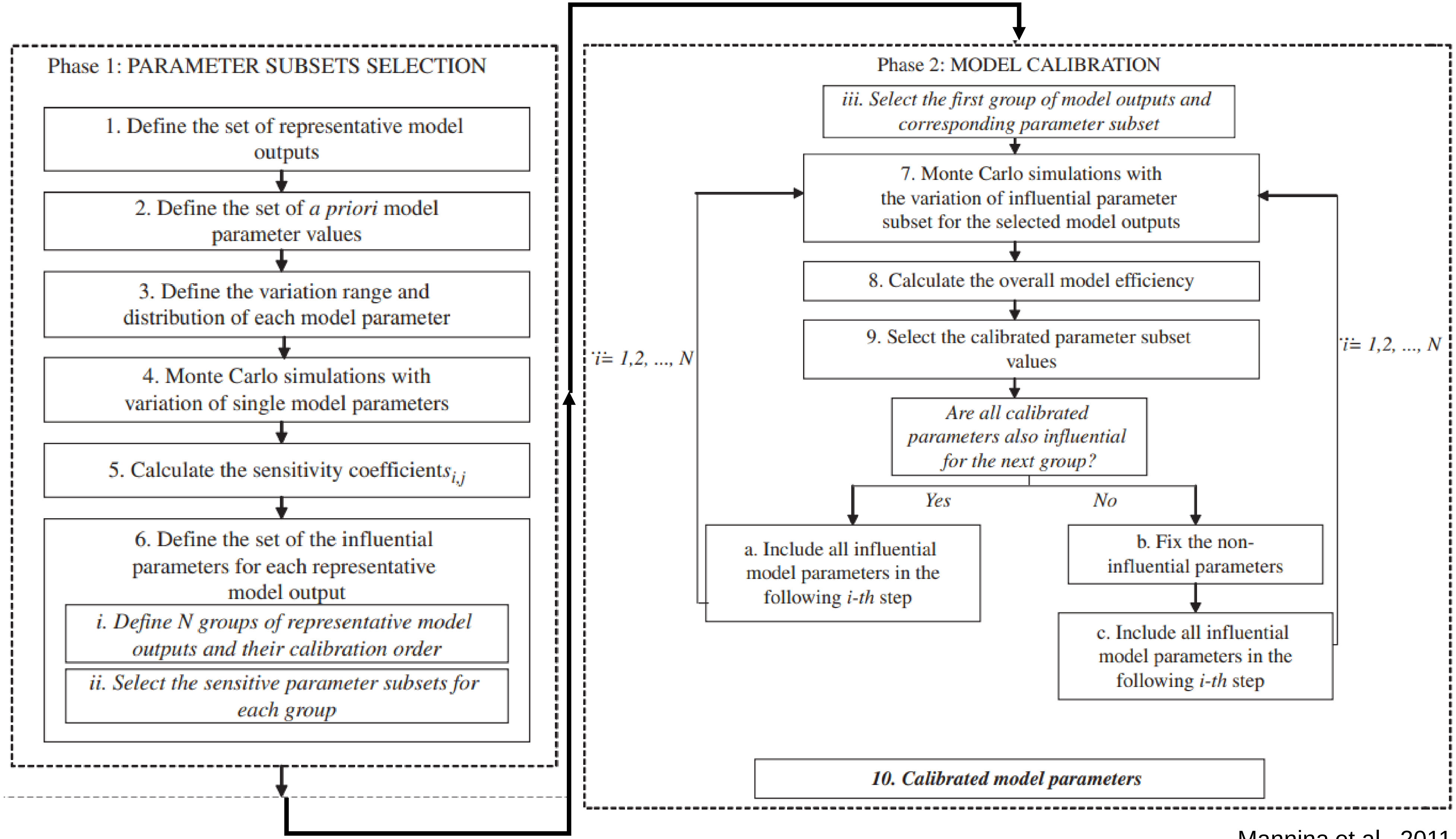
Methodology for Calibration of a Phenomonological Model (Mannina et al. 2011)

Phase I: Parameter Subsets Selection

Sensitivity analysis to reduce the number of model parameters to be calibrated. Different subsets of influential model parameters are selected, each focusing on a different group of output variables.

Phase II: Calibration of Model Parameters Values

The model calibration is performed on the subset of influential parameters by means of a group-wise Monte Carlo technique.



Phase 1: PARAMETER SUBSETS SELECTION

1. Define the set of representative model outputs
2. Define the set of *a priori* model parameter values
3. Define the variation range and distribution of each model parameter
4. Monte Carlo simulations with variation of single model parameters
5. Calculate the sensitivity coefficients$_{i,j}$
6. Define the set of the influential parameters for each representative model output
   - *i. Define N groups of representative model outputs and their calibration order*
   - *ii. Select the sensitive parameter subsets for each group*

Phase 2: MODEL CALIBRATION

iii. Select the first group of model outputs and corresponding parameter subset

7. Monte Carlo simulations with the variation of influential parameter subset for the selected model outputs
8. Calculate the overall model efficiency
9. Select the calibrated parameter subset values

Are all calibrated parameters also influential for the next group?

Yes

a. Include all influential model parameters in the following *i-th* step

No

b. Fix the non-influential parameters

c. Include all influential model parameters in the following *i-th* step

i= 1,2, ..., N

i= 1,2, ..., N

10. Calibrated model parameters

Mannina et al., 2011

Online Data Quality Analysis programmed in MATLAB
(Alferes & Vanrolleghem, 2016)

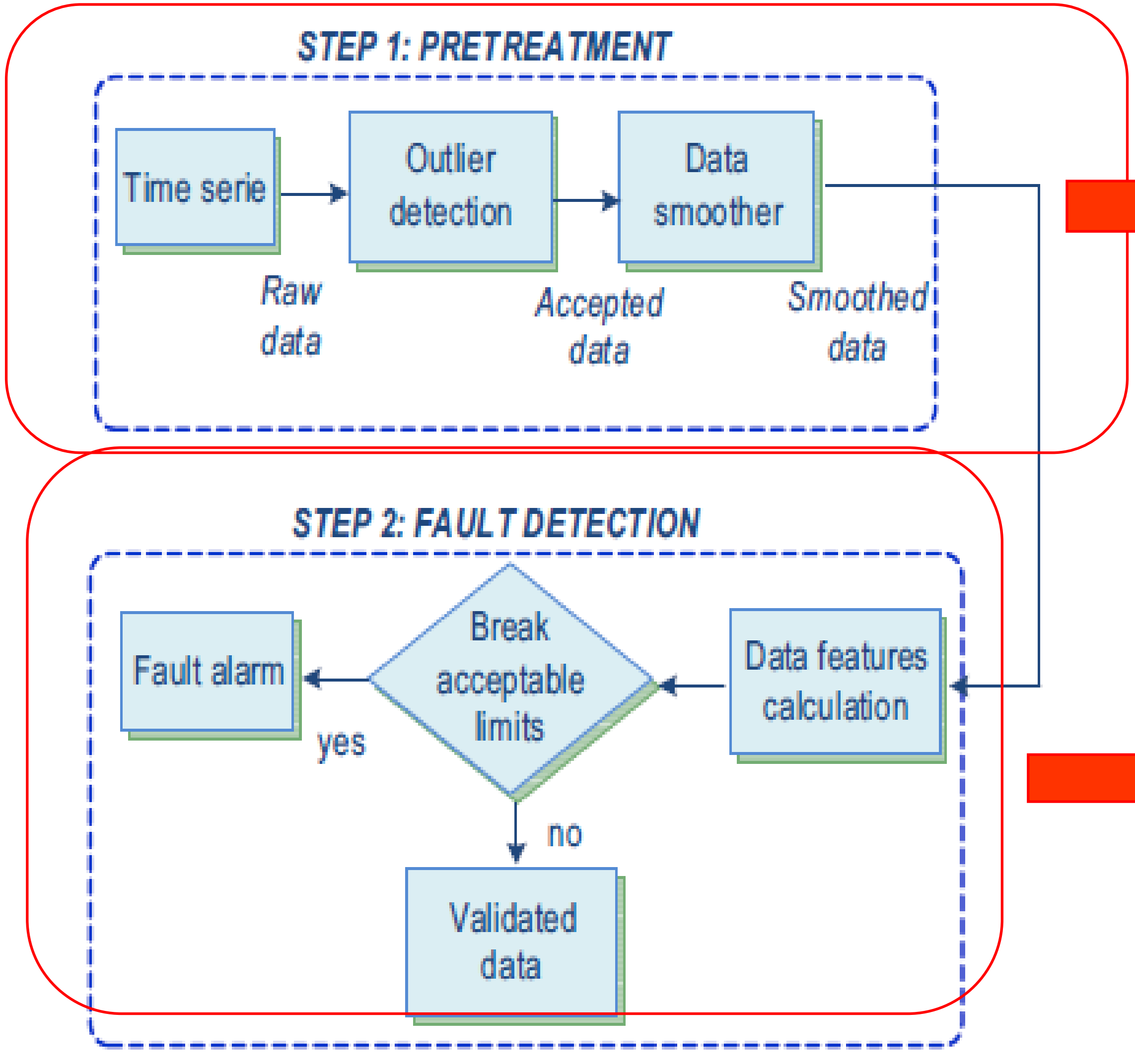
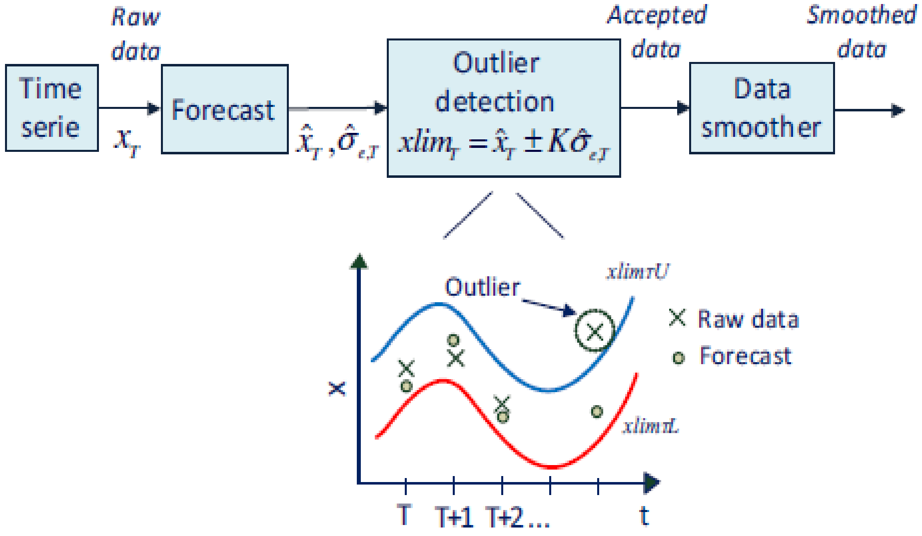
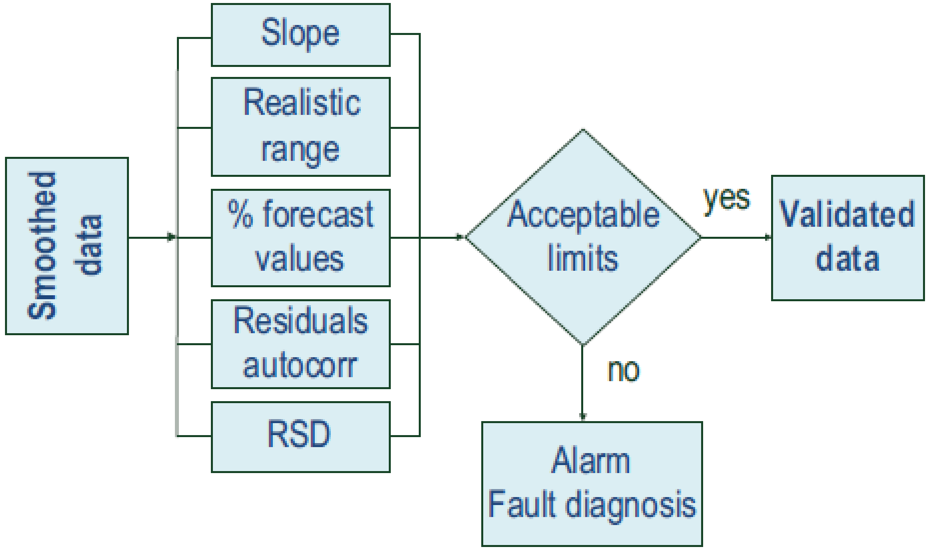


Fig. 1. Univariate time series analysis

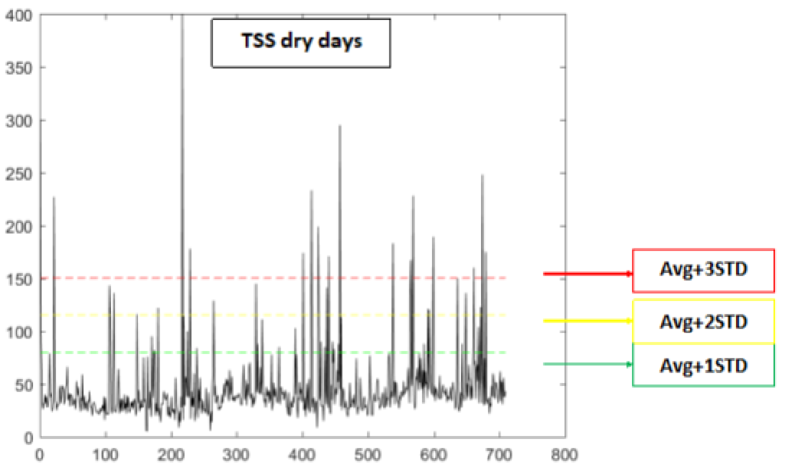


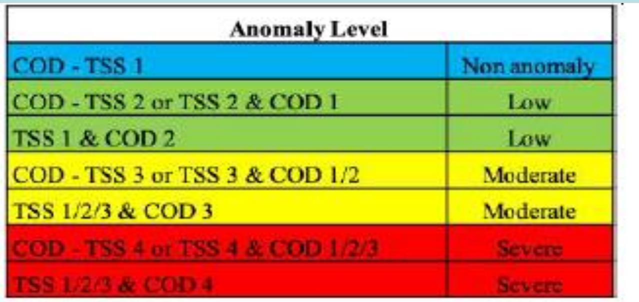


Alferes & Vanrolleghem (2016)

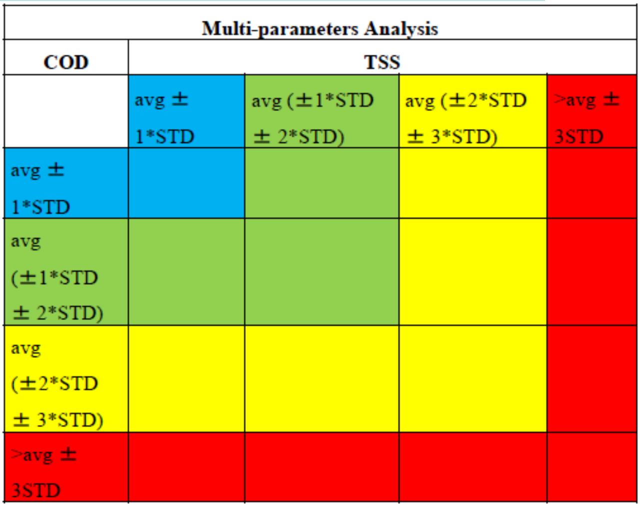
advanced data analysis

W-SMART studied Support Vector Machines (SVM) for predictions of COD & TSS values in effluent Chemically Enhanced Settler => SVM was able to recognize patterns and assign data to the category "anomaly" or "non-anomaly", making it a non-probabilistic binary linear classifier (Tinelli , 2019)

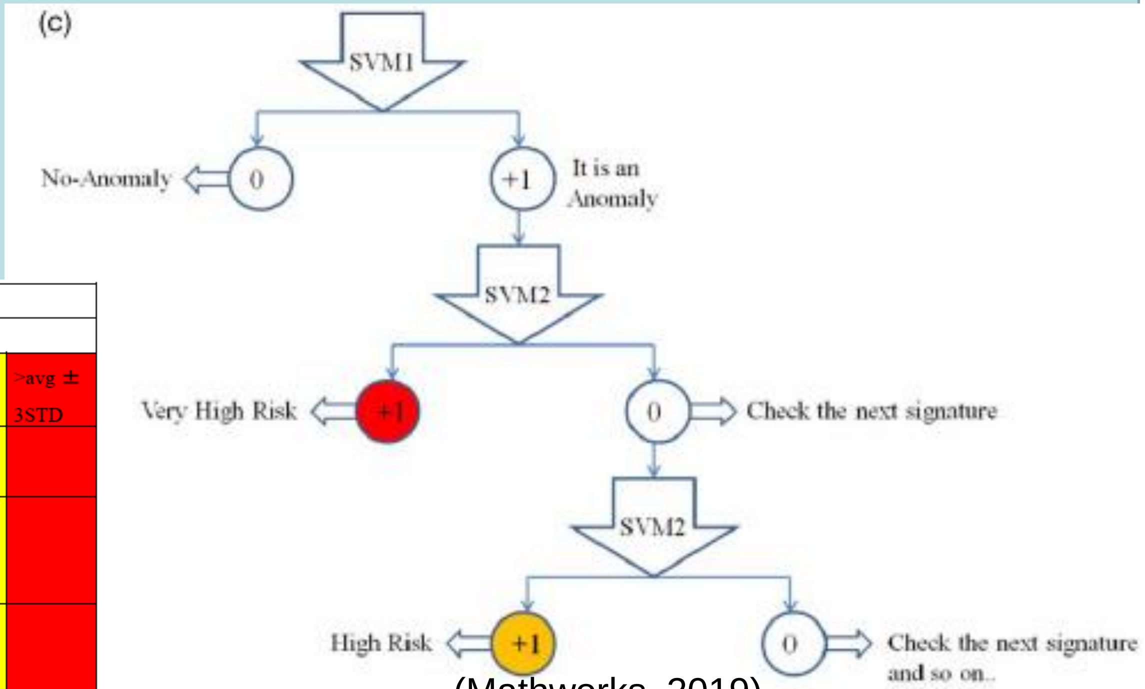




Anomaly Level	
COD - TSS 1	Non anomaly
COD - TSS 2 or TSS 2 & COD 1	Low
TSS 1 & COD 2	Low
COD - TSS 3 or TSS 3 & COD 1/2	Moderate
TSS 1/2/3 & COD 3	Moderate
COD - TSS 4 or TSS 4 & COD 1/2/3	Severe
TSS 1/2/3 & COD 4	Severe



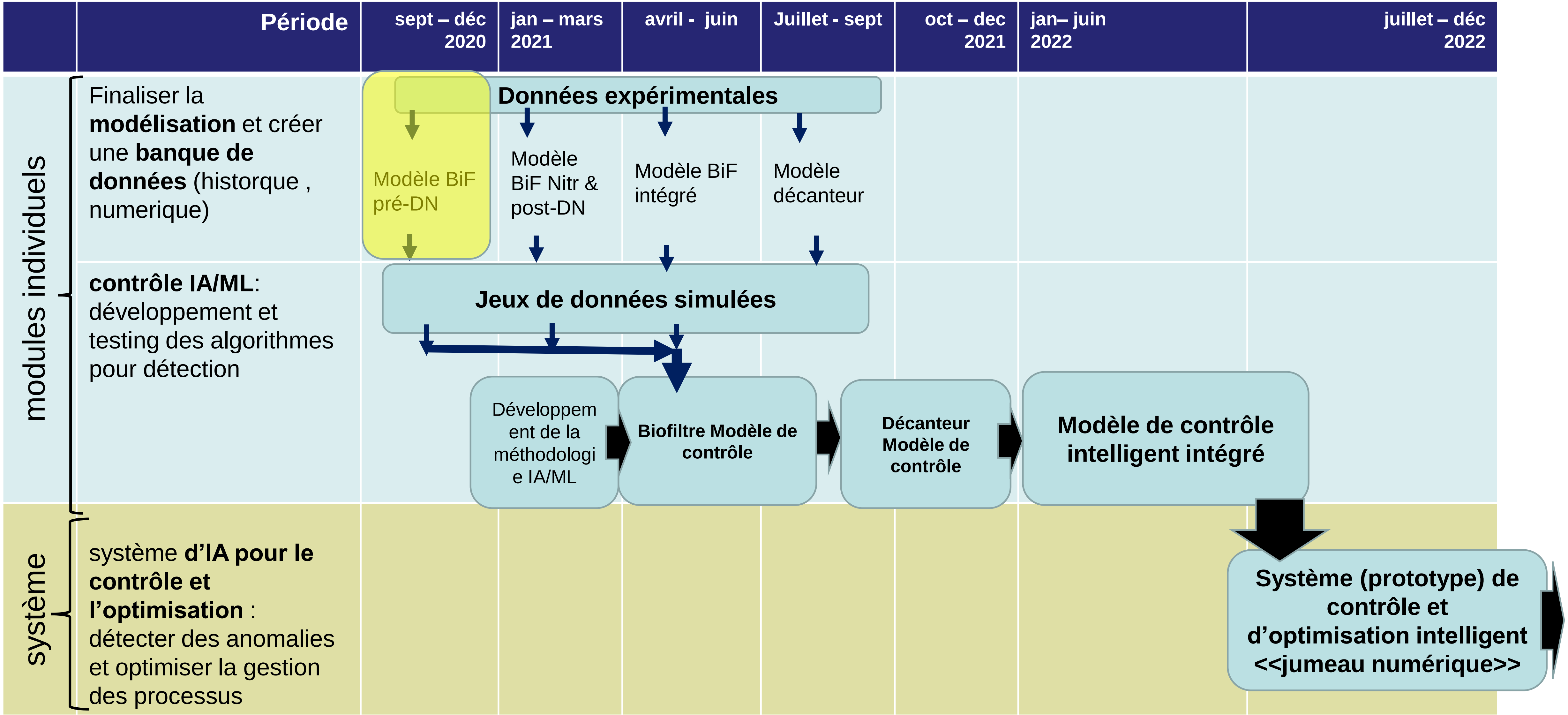
Multi-parameters Analysis				
COD	TSS			
	avg ± 1*STD	avg (±1*STD ± 2*STD)	avg (±2*STD ± 3*STD)	>avg ± 3STD
avg ± 1*STD	🟦	🟩	🟨	🟥
avg (±1*STD ± 2*STD)	🟩	🟩	🟨	🟥
avg (±2*STD ± 3*STD)	🟨	🟨	🟨	🟥
>avg ± 3STD	🟥	🟥	🟥	🟥



(Mathworks, 2019)

Tinelli, 2019

Planification de la méthodologie détaillée



	Période	sept – déc 2020	jan – mars 2021	avril - juin	Juillet - sept	oct – dec 2021	jan– juin 2022	juillet – déc 2022

modules individuels

Finaliser la **modélisation** et créer une **banque de données** (historque , numerique)

Données expérimentales

Modèle BiF pré-DN

Modèle BiF Nitr & post-DN

Modèle BiF intégré

Modèle décanteur

contrôle IA/ML: développement et testing des algorithmes pour détection

Jeux de données simulées

Développement de la méthodologie IA/ML

Biofiltre Modèle de contrôle

Décanteur Modèle de contrôle

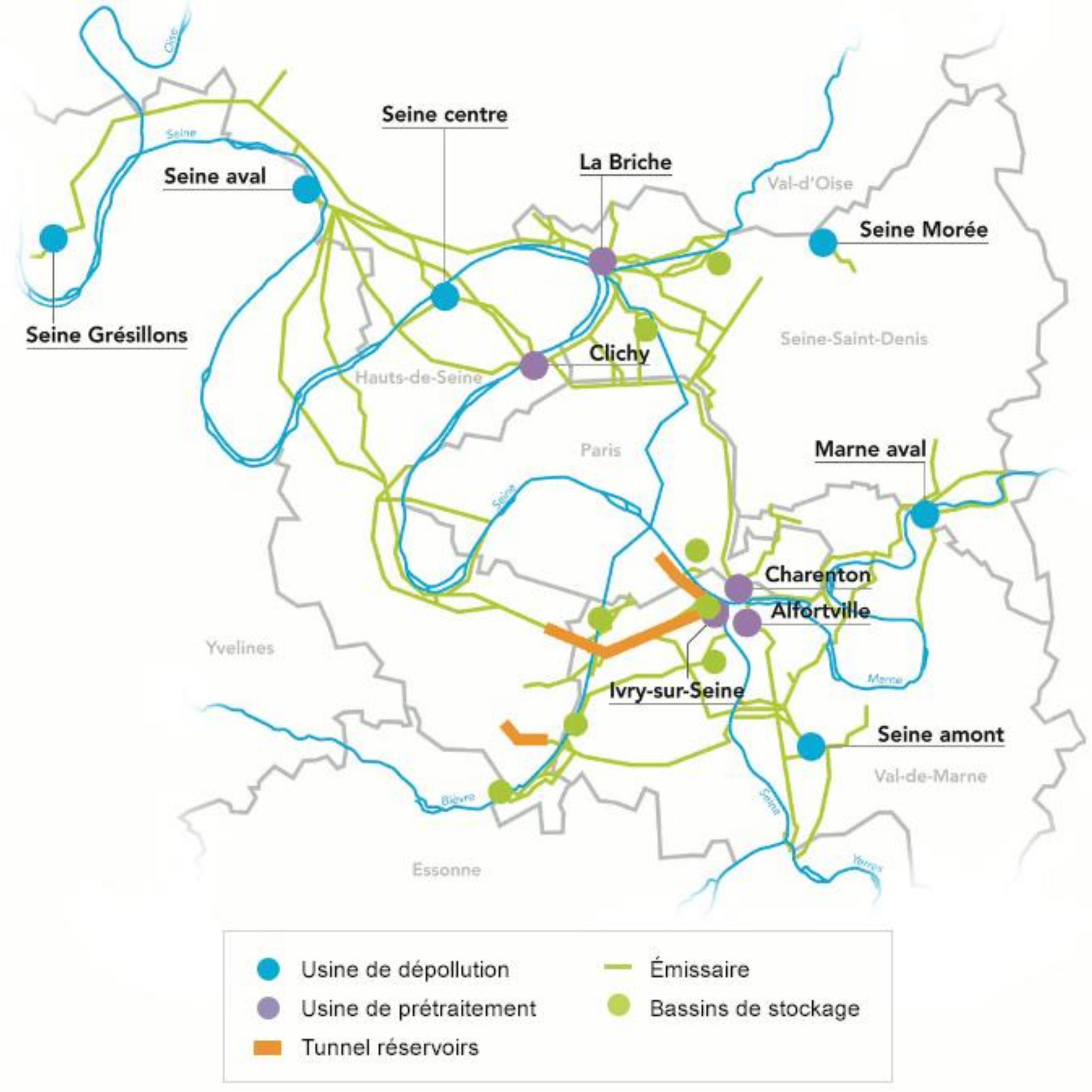
Modèle de contrôle intelligent intégré

système

système **d'IA pour le contrôle et l'optimisation** : détecter des anomalies et optimiser la gestion des processus

Système (prototype) de contrôle et d'optimisation intelligent <<jumeau numérique>>

Site pilot – Seine-Aval (Achères)



WEST Biofiltration Model (Zhu, 2020)

WEST is a dynamic modelling and simulation software of wastewater treatment plants, rivers, sewers and urban

ca

It

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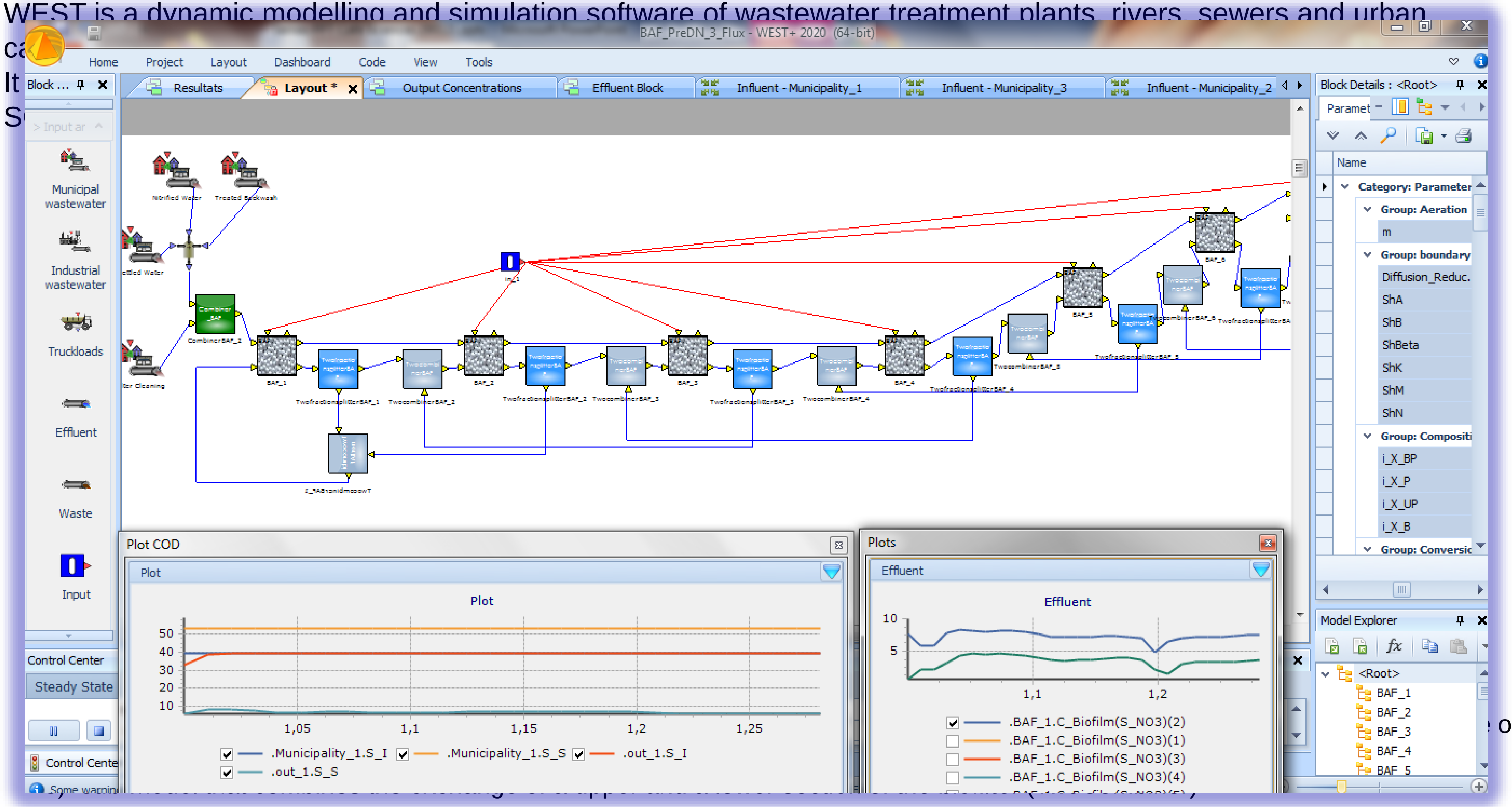
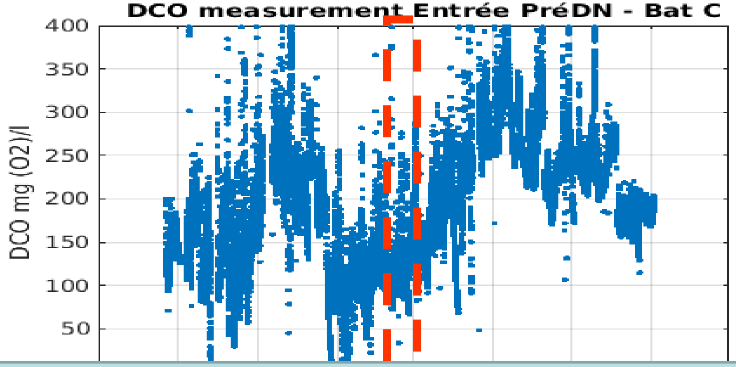
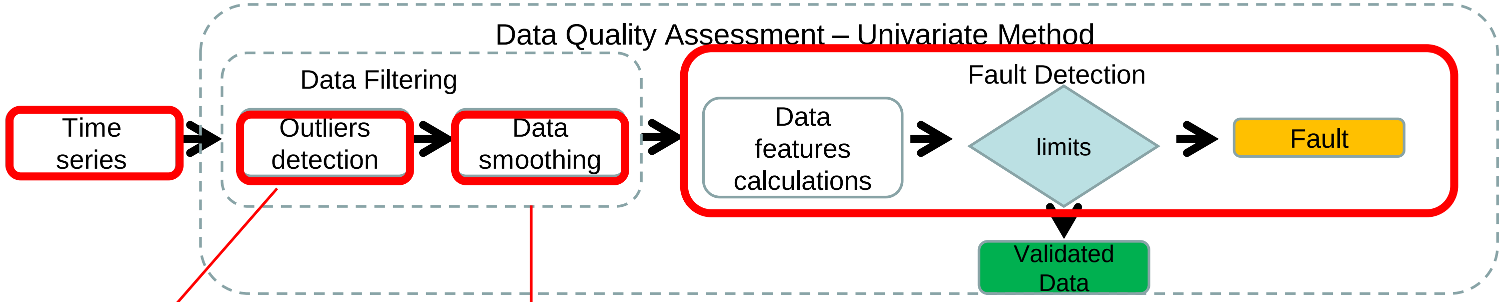


of biofilm

Zhu, 2021

Premiers résultats de Data Quality Assessment DCO total




Data Quality Assessment – Univariate Method

Time series

Data Filtering

Outliers detection

Data smoothing

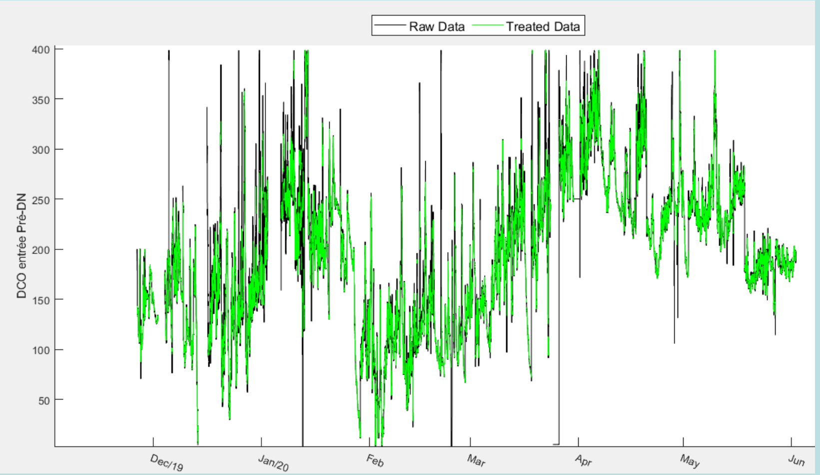
Fault Detection

Data features calculations

limits

Fault

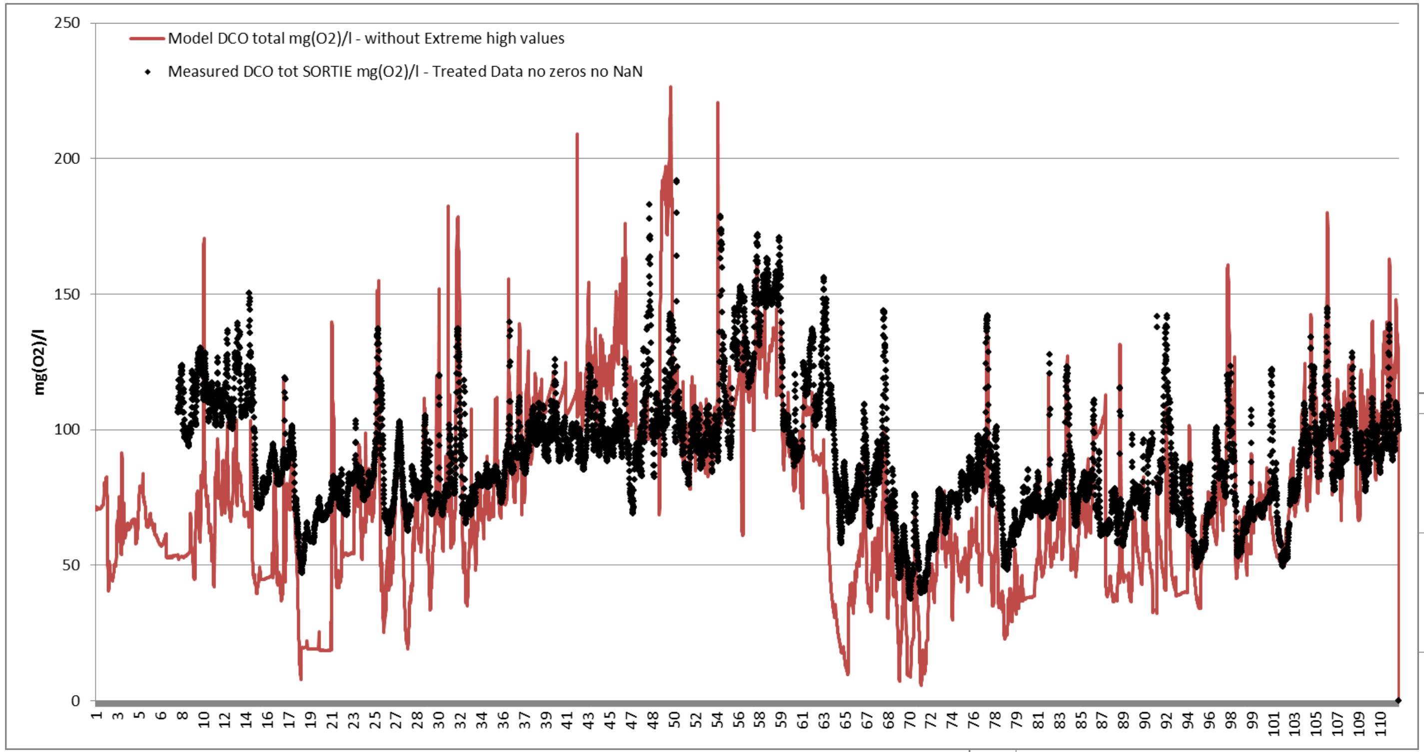
Validated Data



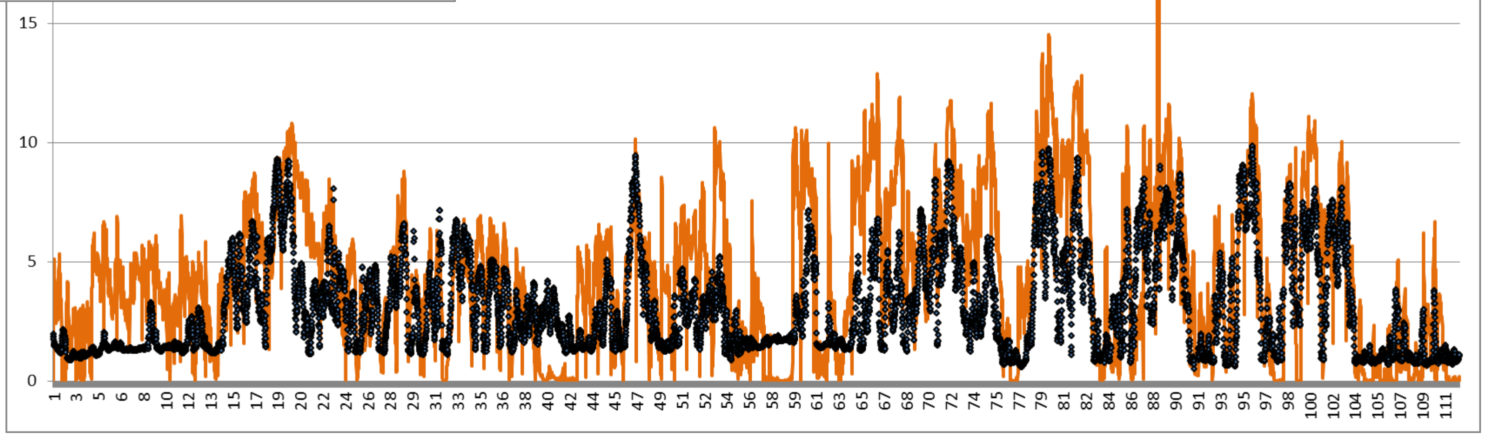
% Outliers detected : 1,8

% Losing Data : 10,5

Premiers résultats de la calibration du modèle



Model calibration for Biofiltration
CODtot effluent



Model calibration for Biofiltration
NO_2 + NO_3 effluent

Lessons learned sofar & next steps

- **Data quality** is an important issue : regular maintenance & calibration of sensors
- Data **collection for longer** periods is necessary to train algorithms
- Modular approach is not easy to overcome : interconnectivity between data collection & storage systems, simulation models, online sensors and SCADA system will be important >> **standarized systems needed**!
- Model-based control using Digital Twins is probably more suited for **larger plants with wide fluctuations** in flow rate and pollutants load.
- Conventional controllers (PID and FeedForward) are sufficiently efficient for **smaller plants with less variations** in flow rate and pollutants loads.
- Model-supported control requires signficiant **expertise** and **experience** >> **Training** required to be fully implemented at operations level

Next steps:

- Calibration and Validation of biofiltration and settler models
- Develop and train algorithms for biofiltration and settler models

Planned contributions & References

- Smart Monitoring and Wastewater Treatment Process Control in the Paris Region (France). *M. Serrao[1, 4], V. Rocher[2], S. Azimi[2], J. Bernier[2], I. Juran[1], P. Vanrolleghem[3], B. Tassin[4] ; (2021) .* Draft under review. Chapter in UNESCO / W-SMART book on ‘Smart Water Management’.

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- Bernier J., Rocher V., Guérin S., Lessard P. (2014b): Modelling of a carbon removal biological aerated filter doing partial nitrification during large-scale secondary treatment; Water Quality Research Journal of Canada ; 49, 3 : 245-257.
- Garrido-Baserba, M., Corominas, L., Cortés, U., Rosso, D., & Poch, M. (2020). The fourth-revolution in the water sector encounters the digital revolution. Environmental Science & Technology, 54(8), 4698-4705.
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- Tabuchi, J.P, Tassin B., Blatrix C. (2016) Greater Paris Water and global change, Water megacities and global change, Portraits of 15 emblematic Cities of the World, UNESCO/ARCEAU.
- Therrien, J. D., Nicolaï, N., & Vanrolleghem, P. A. (2020). A critical review of the data pipeline: how wastewater system operation flows from data to intelligence. Water Science and Technology.
- Tinelli, S. and Juran, I. (2019a). Tertiary physico-chemical settling during wastewater treatment: multi-criteria optimization of chemical dosage. Artificial Intelligence Application for WasteWater Treatment Process .
- Zhu, J., Bernier, J., Pauss, A., Vanrolleghem, P. A., Rocher, V. (2018a) Modélisation de la station Seine Aval–Vers une optimisation en temps réel des coûts d’exploitation et environnementaux. Présentation Journée Information Eaux, Poitiers

Merci pour votre attention.

Questions ?

marcello.serrao@enpc.fr
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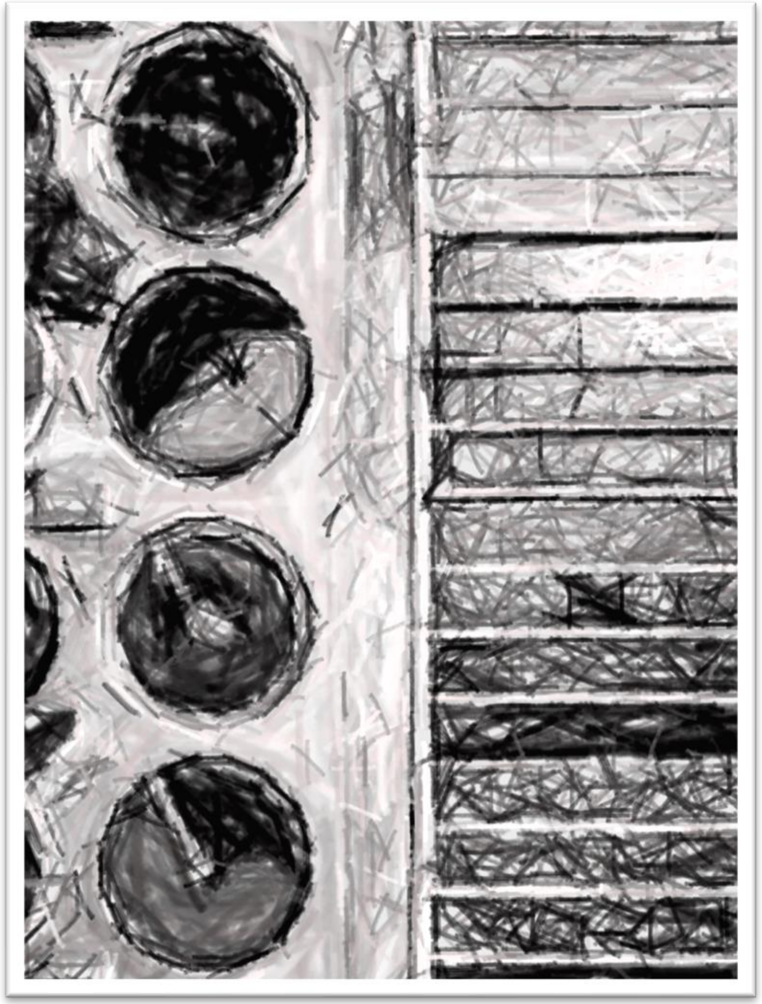
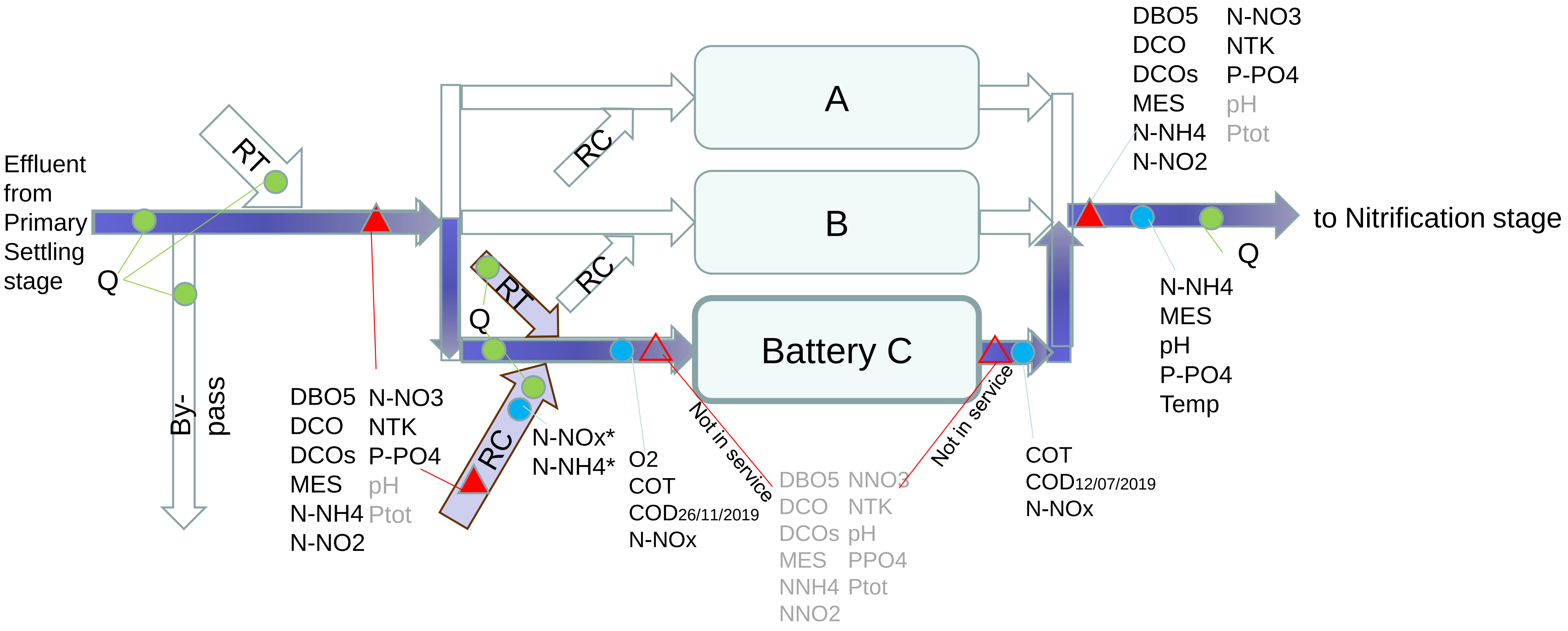


Ivan Bandura

- Extra slides

Méthodologie de la calibration de la PréDN
Step 2 : Data Collection and Reconciliation

Data Collection at PréDN for Battery C – Performance data from BASTA database & monitoring system



Effluent from Primary Settling stage

Q

RT

By-pass

DBO5 N-NO3
DCO NTK
DCOs P-PO4
MES pH
N-NH4 Ptot
N-NO2

Q

RT

RC

N-NOx*
N-NH4*

O2
COT
COD26/11/2019
N-NOx

Not in service

DBO5 NNO3
DCO NTK
DCOs pH
MES PPO4
NNH4 Ptot
NNO2

A

B

Battery C

RC

RC

Not in service

COT
COD12/07/2019
N-NOx

DBO5 N-NO3
DCO NTK
DCOs P-PO4
MES pH
N-NH4 Ptot
N-NO2

to Nitrification stage

Q

N-NH4
MES
pH
P-PO4
Temp

▲ Laboratory 24 hrs composites
●● In-situ measurements 15 min

RC = recirculation of Nitrified water *) measured at entry of PostDN
RT = Retours en Tête = MF + RF = (1) backwash water from filters treated by MultiFlo to reduce suspended solids (TSS) + (2) cooling water from sludge heaters

Mesures Moyennes Journalières PréDénitrification Batterie C

26/11/2019 – 15/03/2020

DP	Lab
DBO5	90
DCO	249
DCOsol	77
MES	120
N-NH4	35
N-NO2	0,25
N-NO3	0,63
NTK	48
P-PO4	1

RC + RF	Lab	Capt
DBO5	9	
DCO	44	
DCOsol	33	
MES	11	
N-NH4	2,5	2,8
N-NO2	0,9	
N-NO3	19,9	19,9 NOx
NTK	4,7	
P-PO4	0,9	

MF	Lab
DBO5	22
DCO	76
DCOsol	44
MES	147*
N-NH4	21
N-NO2	0,3
N-NO3	2,9
NTK	26,6
P-PO4	0,8

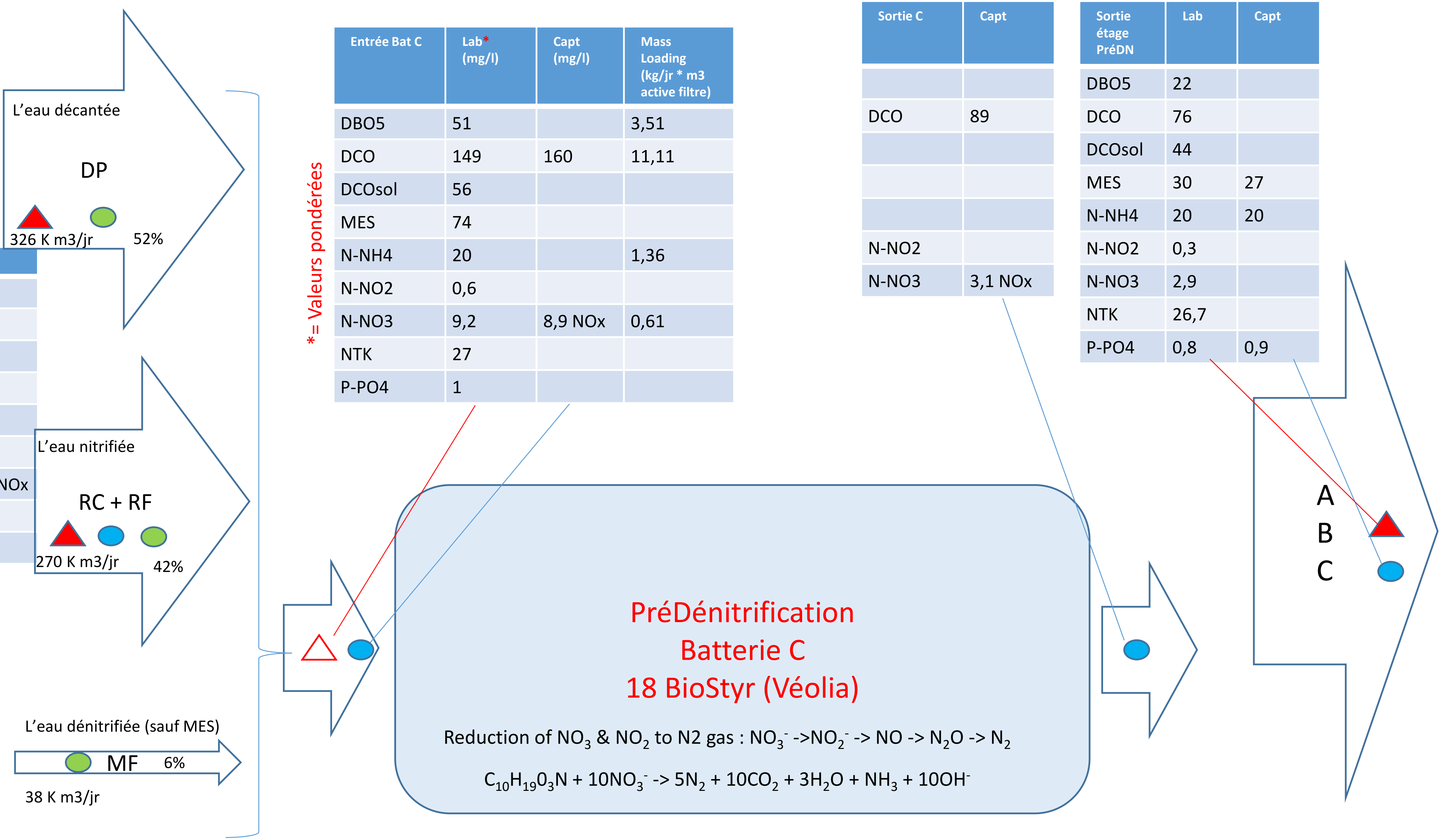
*= mesurés par capteur en ligne

Entrée Bat C	Lab* (mg/l)	Capt (mg/l)	Mass Loading (kg/jr * m3 active filtre)
DBO5	51		3,51
DCO	149	160	11,11
DCOsol	56		
MES	74		
N-NH4	20		1,36
N-NO2	0,6		
N-NO3	9,2	8,9 NOx	0,61
NTK	27		
P-PO4	1		

*= Valeurs pondérées

Sortie C	Capt
DCO	89
N-NO2	
N-NO3	3,1 NOx

Sortie étage PréDN	Lab	Capt
DBO5	22	
DCO	76	
DCOsol	44	
MES	30	27
N-NH4	20	20
N-NO2	0,3	
N-NO3	2,9	
NTK	26,7	
P-PO4	0,8	0,9



L'eau décantée

DP

326 K m3/jr

52%

L'eau nitrifiée

RC + RF

270 K m3/jr

42%

L'eau dénitrifiée (sauf MES)

MF

6%

38 K m3/jr

PréDénitrification

Batterie C

18 BioStyr (Véolia)

Reduction of NO_3 & NO_2 to N2 gas : NO_3^- ->NO_2^- -> NO -> N_2O -> N_2

$C_{10}H_{19}O_3N + 10NO_3^- \rightarrow 5N_2 + 10CO_2 + 3H_2O + NH_3 + 10OH^-$