

From data to decisions: How can AI and big data support decision-making in resource recovery from waste?

Presented by: Cesar Arenas
PhD. Candidate



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Welcome & Agenda

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1.- Introduction

- A wastewater treatment plant (WWTP) involves multiple complex processes that need to be operated seeking for optimal effluent quality and energy efficiency.
- The integration of knowledge from mechanistic models into online operations enables operators to improve overall plant performance in real-time.



Aerial view of DARROW WWTP (Tilburg, Netherlands)



Motivation & Background



Reduce Energy
Consumption



Reduce
Greenhouse Gases



Reduce Waste



Reduce Chemical
Consumption



Increase Water
Quality

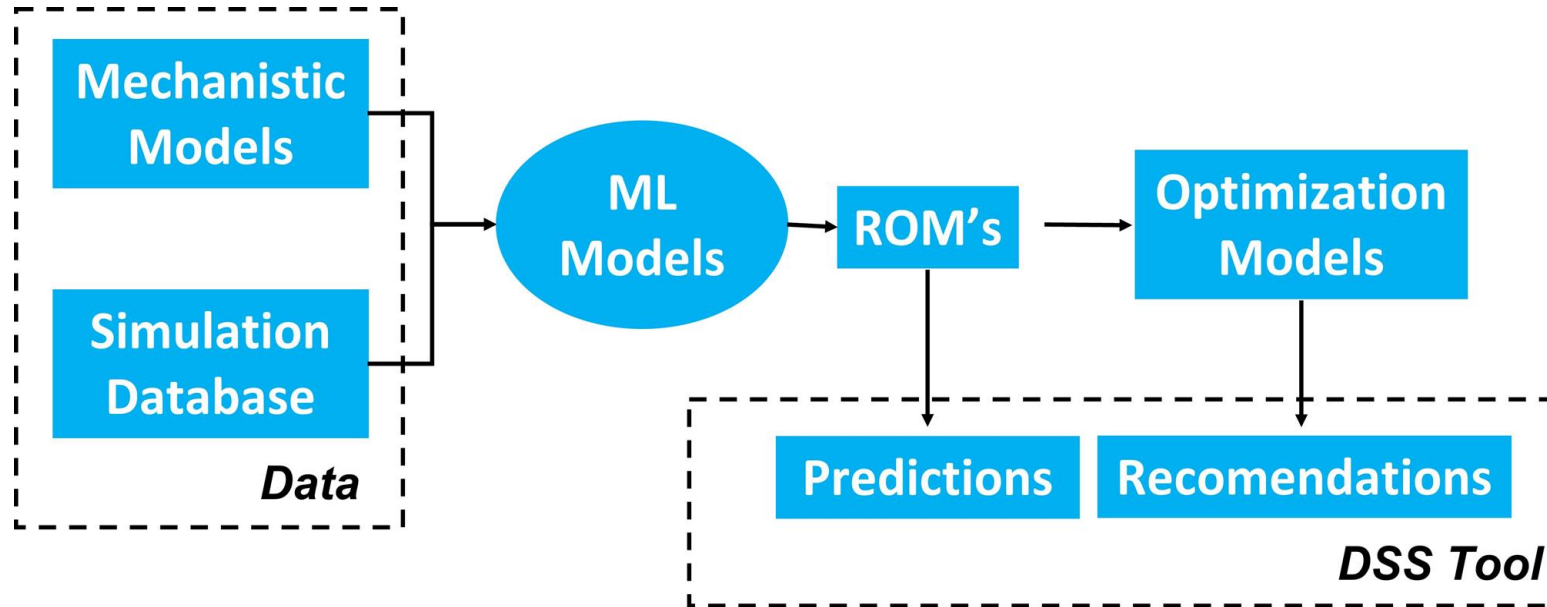
From Waste to Value

- 1.- Influent
- 2.- Grit Chamber
- 3.- Primary Treatment
- 4.- Secondary Treatment
- 5.- Clarifiers
- 6.- UV Desinfection
- 7.- Effluent
- 8.- Sludge Line
- 9.- Anaerobic digestion
- 10.- Dewatering
- 11.- Power Generators

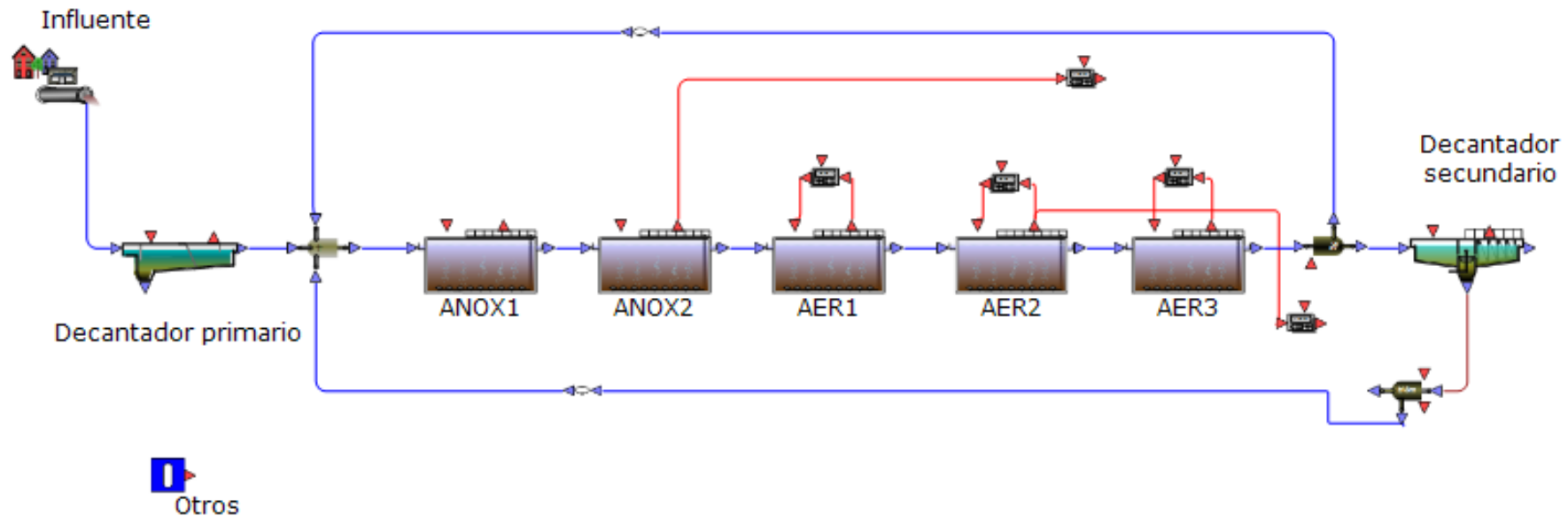
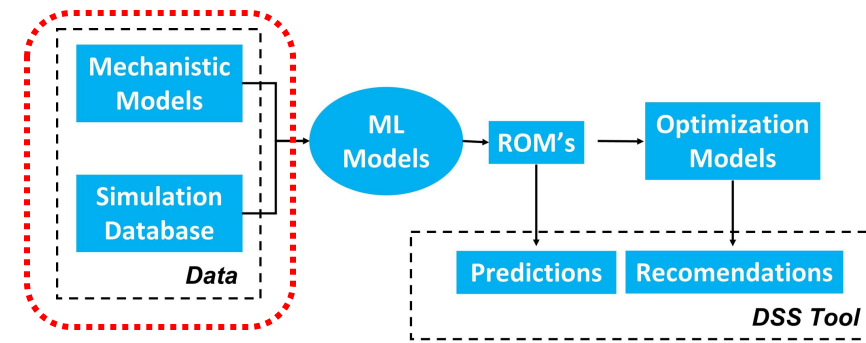


Technical Strategy

Mechanistic models and AI-driven data models are combined to create hybrid systems that enable accurate predictions of key variables related to influent, effluent, sensor readings, and biomass dynamics. This integrated approach leverages the physical understanding of mechanistic models with the adaptive learning capabilities of AI.

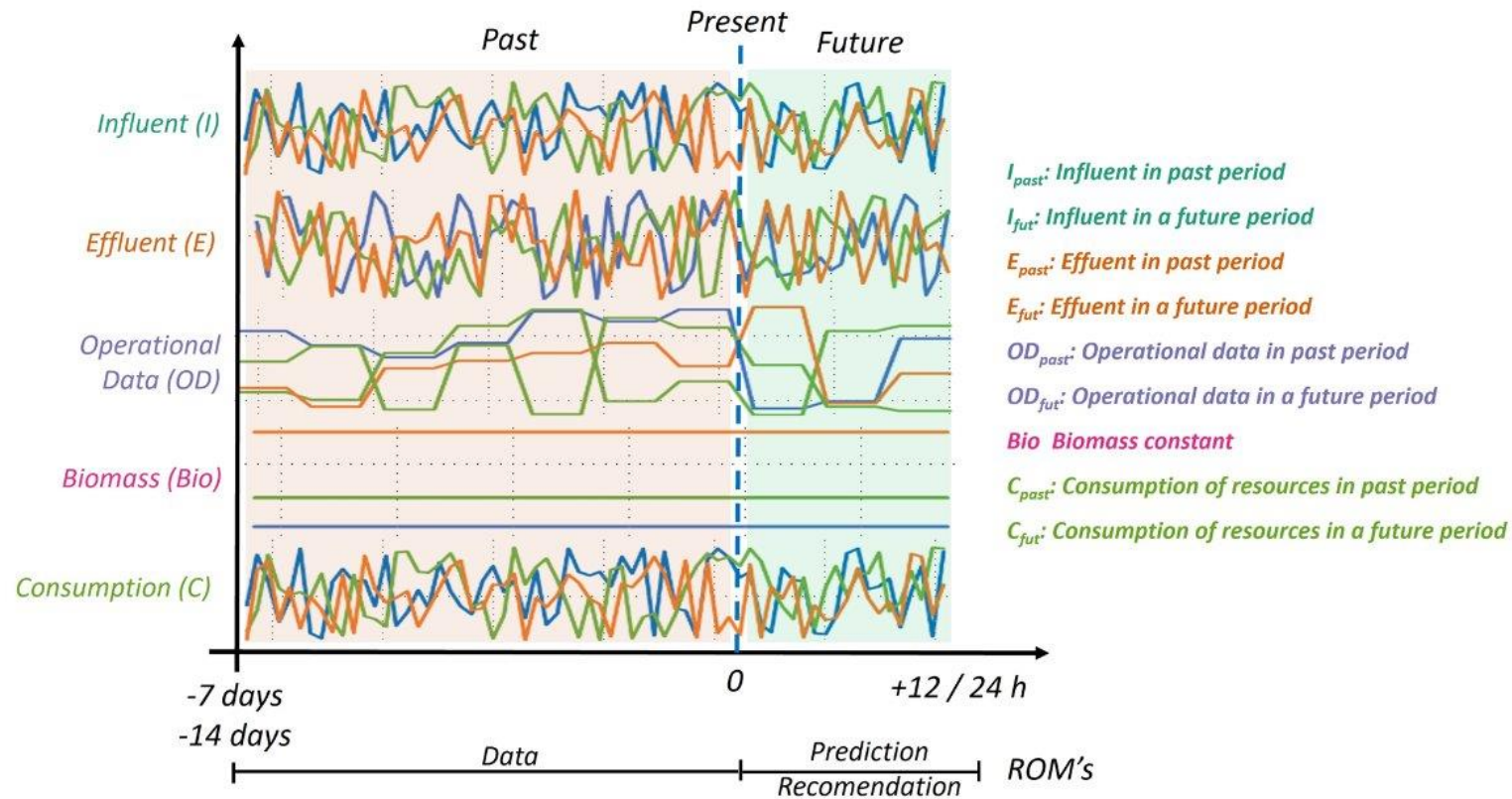
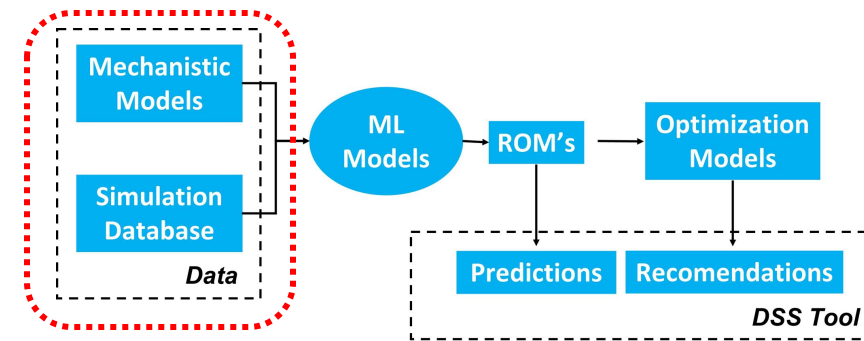


Data Acquisition



Software: WEST
Configuration BSM2
Data Frequency: Hourly
Influent Scenarios: 6

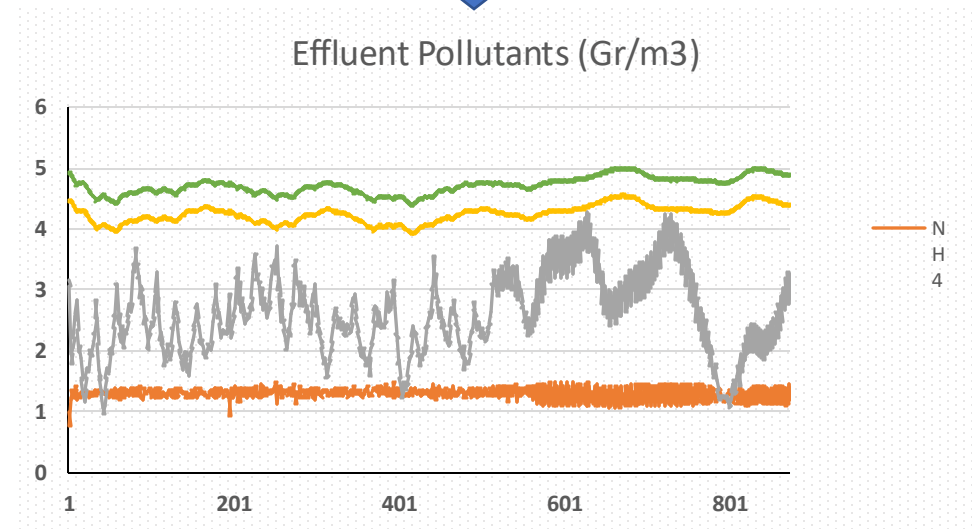
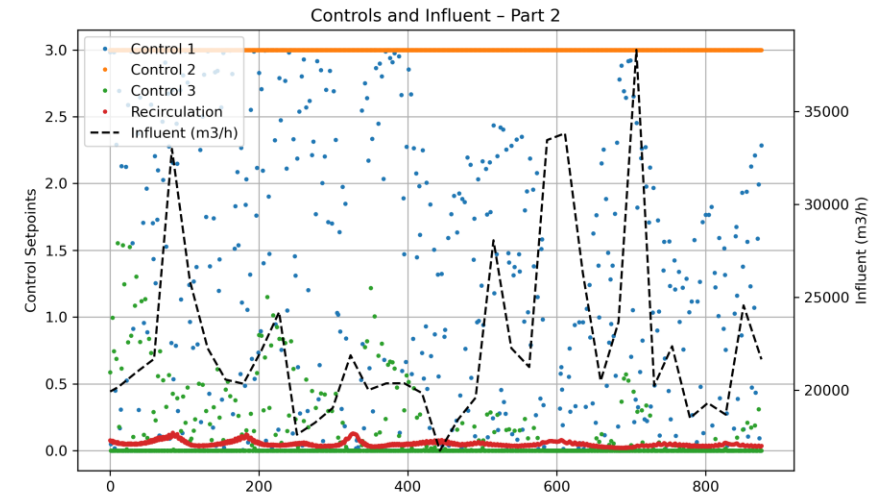
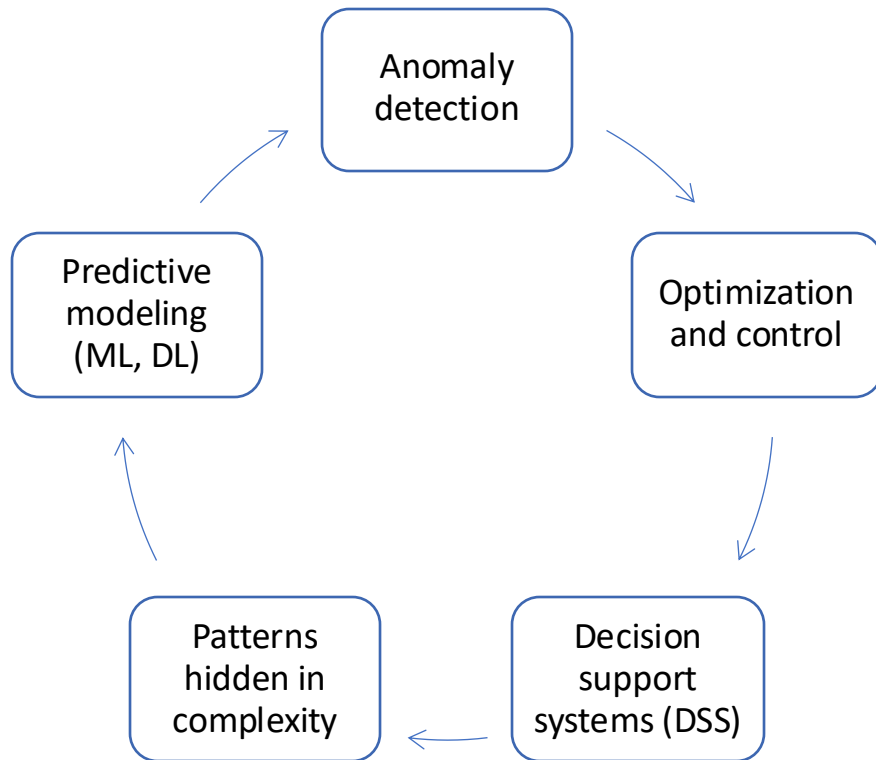
Data Acquisition



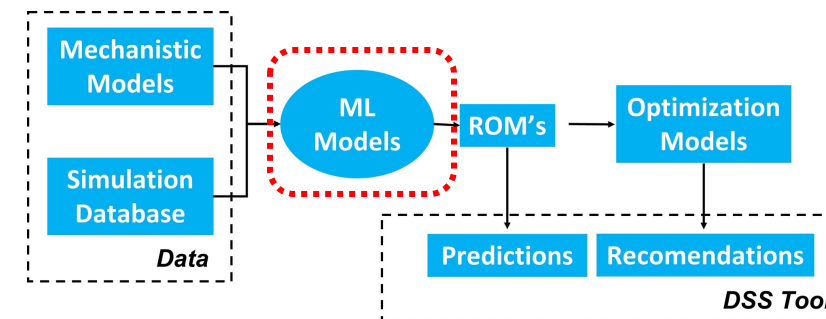
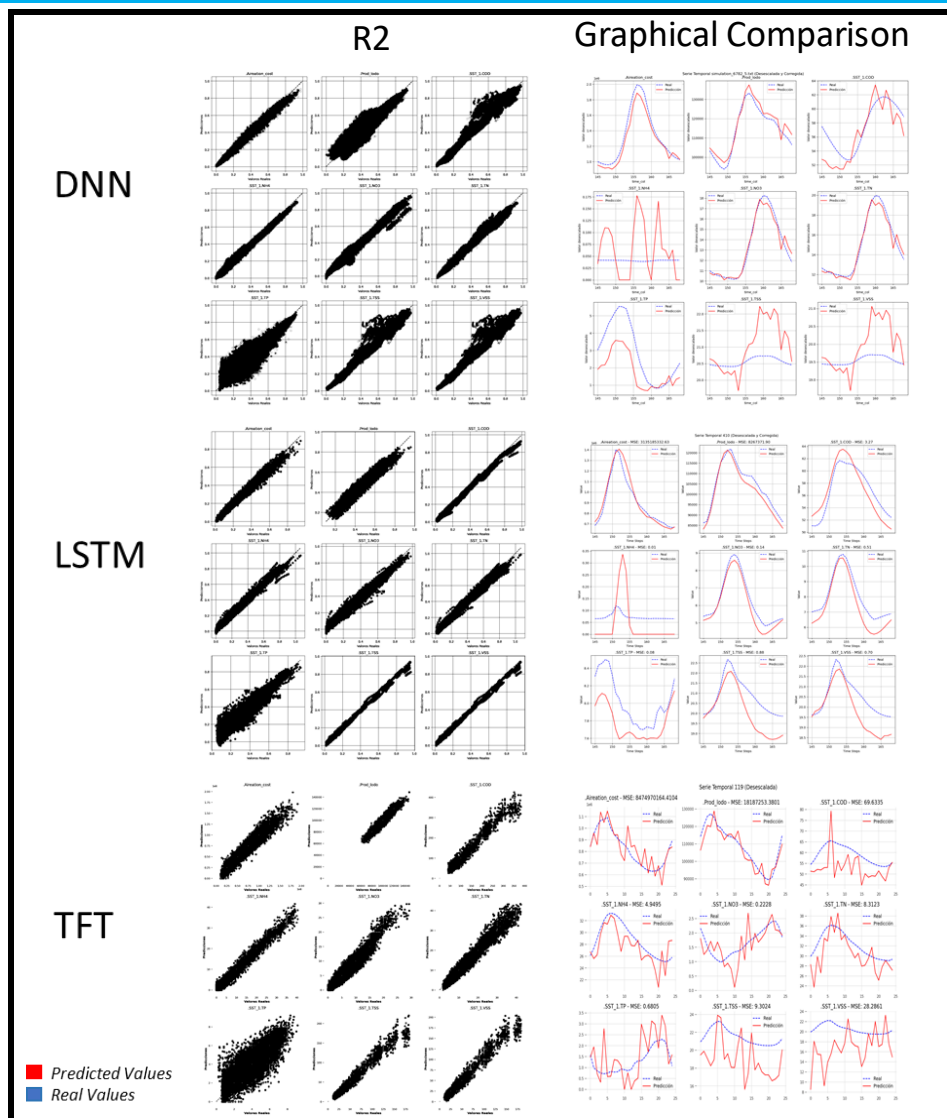
$$(E_{fut}, C_{fut}) = f(I_{past}, I_{fut}, E_{past}, OD_{past}, OD_{fut}, Bio) \quad \rightarrow \text{Prediction}$$

$$OD_{fut} = f(I_{past}, I_{fut}, E_{past}, E_{fut}, OD_{past}, Bio) \quad \rightarrow \text{Recomendation}$$

What AI Brings?

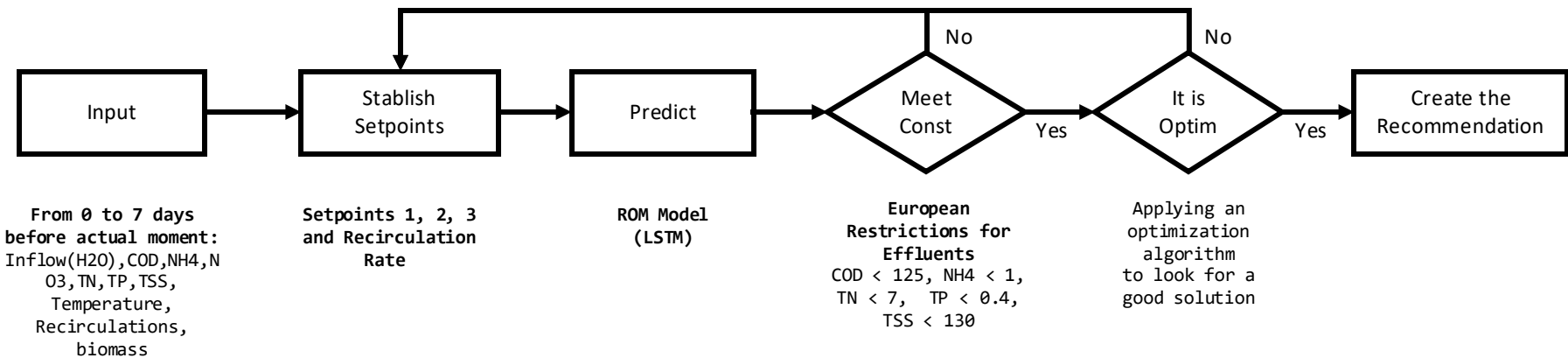
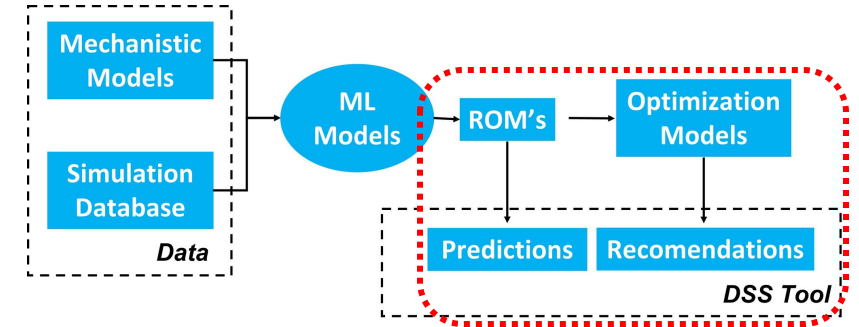


ML Model

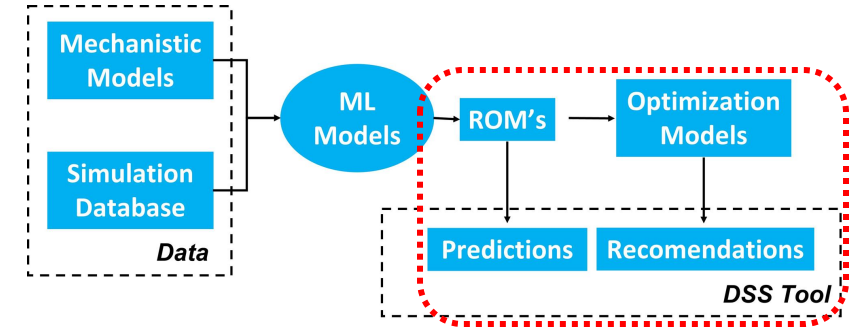


For a future recommendation system, **DNN** is a good choice as it achieves the **lowest errors (MSE)** and **high R^2 values**, making it stable and accurate model. **LSTM** is a strong alternative if the system needs to capture **time-based dependencies**, as it handles sequential patterns effectively. **TFT**, while **interpretable**, shows **higher errors** and lower R^2 compared to DNN and LSTM.

DSS Tool - Strategy



DSS Tool – Strategy



Final Optimization Problem

$$\min_{\mathbf{u}} \quad \mathbf{F}(\mathbf{u}) = [-\text{EQI}(\mathbf{u}), \quad \text{OCI}(\mathbf{u}), \quad -\text{CH}_4(\mathbf{u})]$$

1. Effluent Quality Index (EQI)

$$\text{EQI} = \frac{1}{1000} \sum_{t=1}^{24} Q_e(t) \cdot (2 \cdot \text{TSS}(t) + \text{COD}(t) + 30 \cdot \text{TKN}(t) + 10 \cdot \text{NO}_3(t))$$

2. Operational Cost Index (OCI)

$$\text{OCI} = \frac{1}{24} \sum_{t=1}^{24} (\text{AE}(t) + 3 \cdot \text{SP}(t))$$

3. Methane Production (CH_4)

$$\text{CH}_4 = \frac{16 \cdot P_{\text{atm}}}{R \cdot T_{\text{ad}}} \sum_{t=1}^{24} \left(\frac{Q_{\text{gas}}(t) \cdot p_{\text{CH}_4}}{P_{\text{gas}}} \right)$$

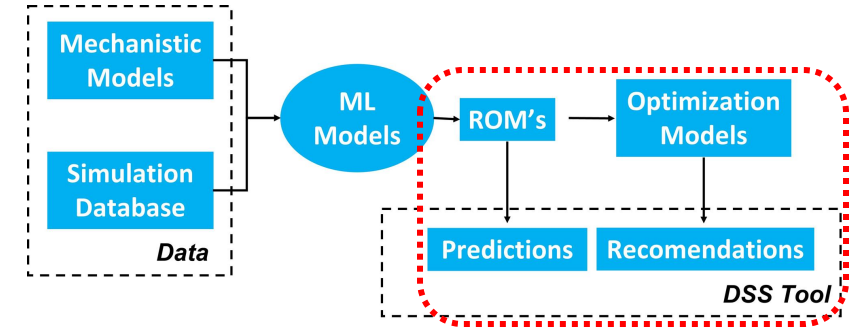
- $t = 1, \dots, 24$ (forecast horizon in hours)
- $Q_e(t)$: Effluent flow [m^3/h]
- $\text{COD}(t), \text{TKN}(t), \text{NO}_3(t), \text{TSS}(t)$: Effluent pollutants [g/m^3]
- $\text{AE}(t)$: Aeration cost [$\text{€}/\text{h}$]
- $\text{SP}(t)$: Sludge cost [$\text{€}/\text{h}$]
- $Q_{\text{gas}}(t)$: Biogas flow [m^3/h]
- Constants:

$$p_{\text{CH}_4} = 0.65,$$

$$P_{\text{atm}} = 1.01325 \text{ bar},$$

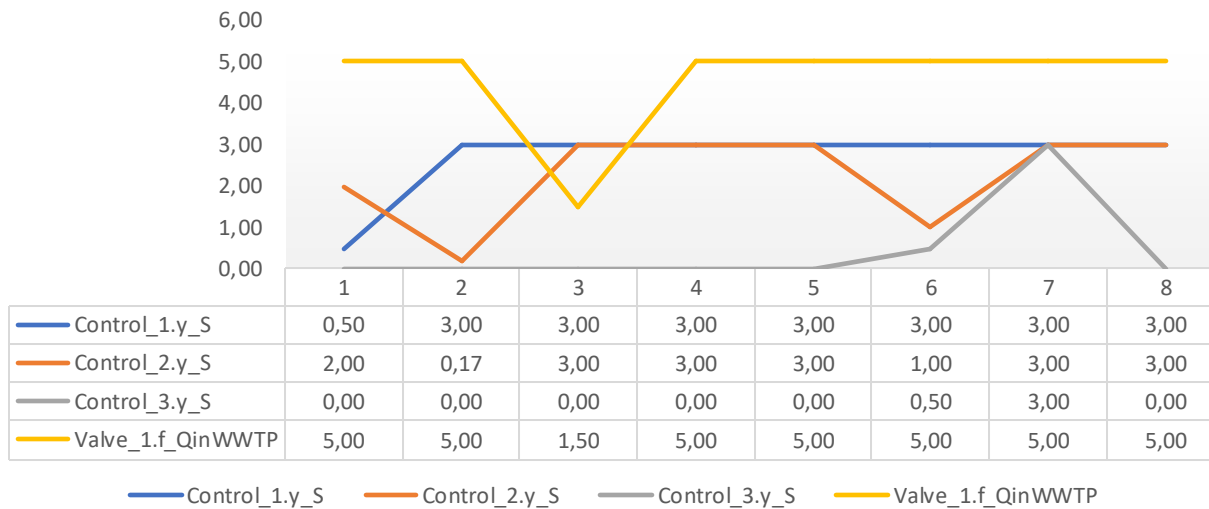
$$R = 0.08314 \text{ bar} \cdot \text{m}^3/(\text{mol} \cdot \text{K})$$

DSS Tool - Strategy

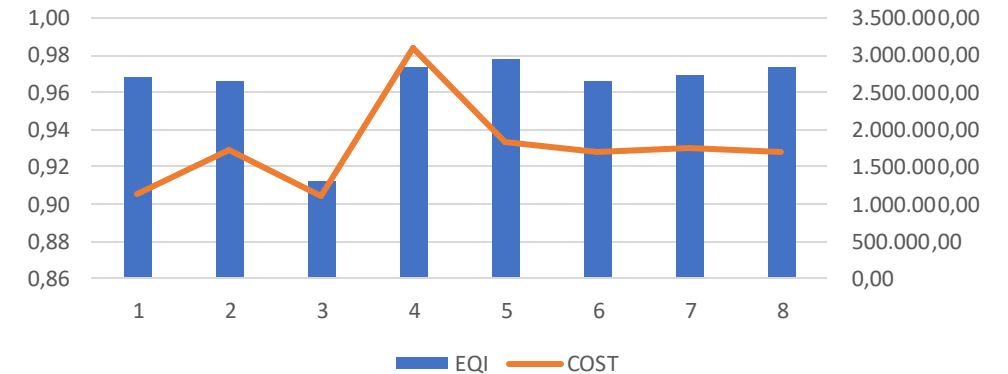


Examples for first results representation

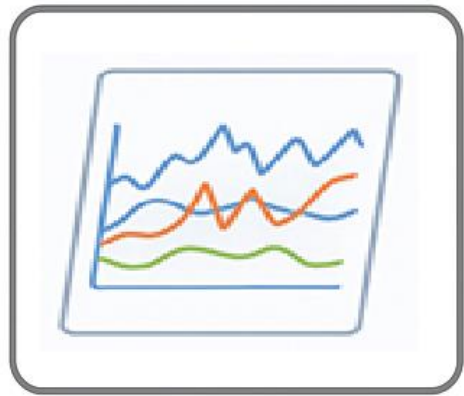
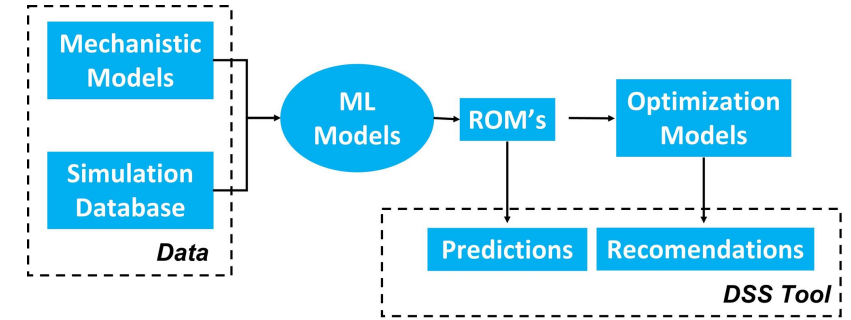
Recommended Setpoints for the next 8 hours



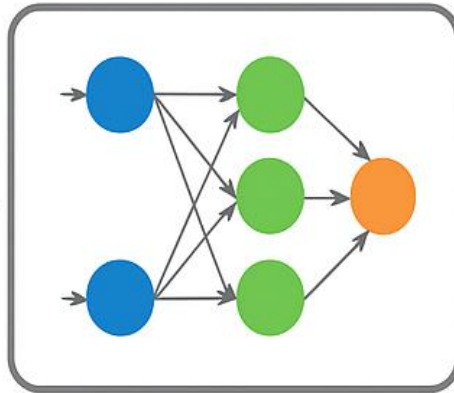
EQI and COST



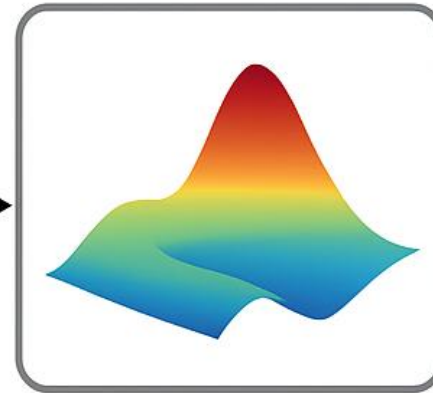
DSS Tool - Strategy



Input (7 days)



Predict



Optimization



Good Results



Benefits

- DARROW aims to build and demonstrate an innovative, optimised, modular, and flexible data-driven AI solution to make existing WWTPs more autonomous, more energy efficient and better prepared for their transformation into WRRFs.
- Practical use: energy savings, process stability, resource recovery.
- Simpler decision-making, less trial-and-error.

References

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