

Integrated hybrid modelling of water resource recovery facilities by coupling mechanistic and data-driven ODE models

W. Quaghebeur^{1,2}, E. Torfs¹, B. De Baets², I. Nopens¹

¹BIOMATH, Department of Data Analysis and Mathematical Modelling, Faculty of Bioscience Engineering, Ghent University, Coupure links 653, 9000 Ghent, Belgium

²KERMIT, Department of Data Analysis and Mathematical Modelling, Faculty of Bioscience Engineering, Ghent University, Coupure links 653, 9000 Ghent, Belgium

Problem

Water treatment plant operators want to apply models online as a *digital twin*. To be useful, these models need to be able to make accurate predictions and extrapolate to unknown data. The currently used techniques either **lack accuracy** (mechanistic models) or **fail to extrapolate** (data-driven models).

Mechanistic models

- Incorporate physical and empirical knowledge (e.g. mass balances, conversion rates, ...)
- E.g. Activated Sludge Models (ASM)
- Formulated as differential equations

$$\frac{d\mathbf{X}_t}{dt} = f(\mathbf{X}_t)$$

- + Interpretable
- + Can extrapolate to unseen data
- **Domain knowledge is incomplete** and a **simplification** of the underlying system
E.g., CSTR instead of mixing, simplifying microbial communities, ...

Data-driven models

- Search for relationships in available data
- Different *machine learning* techniques, e.g. artificial neural networks, random forests
- Here formulated as neural differential equations

$$\frac{d\mathbf{X}_t}{dt} = nn(\mathbf{X}_t)$$

- Black-box
- **Fail to extrapolate** to unseen data
- + No domain knowledge needed
- + Leverage all available data
- + Accurate

Hybrid models

Combine a mechanistic and data-driven model

$$\frac{d\mathbf{X}_t}{dt} = \underbrace{f(\mathbf{X}_t)}_{\text{mechanistic}} + \underbrace{nn(\mathbf{X}_t)}_{\text{data-driven}}$$

- Hybrid models can make **accurate predictions**, without complete domain knowledge or a representative dataset.
- The data-driven part learns the **dynamics not incorporated** by the mechanistic part.

The strengths of both models are combined:

- The data-driven part fills in the gaps in domain knowledge of the mechanistic model
- The mechanistic model fills in the gaps in the dataset of the data-driven model

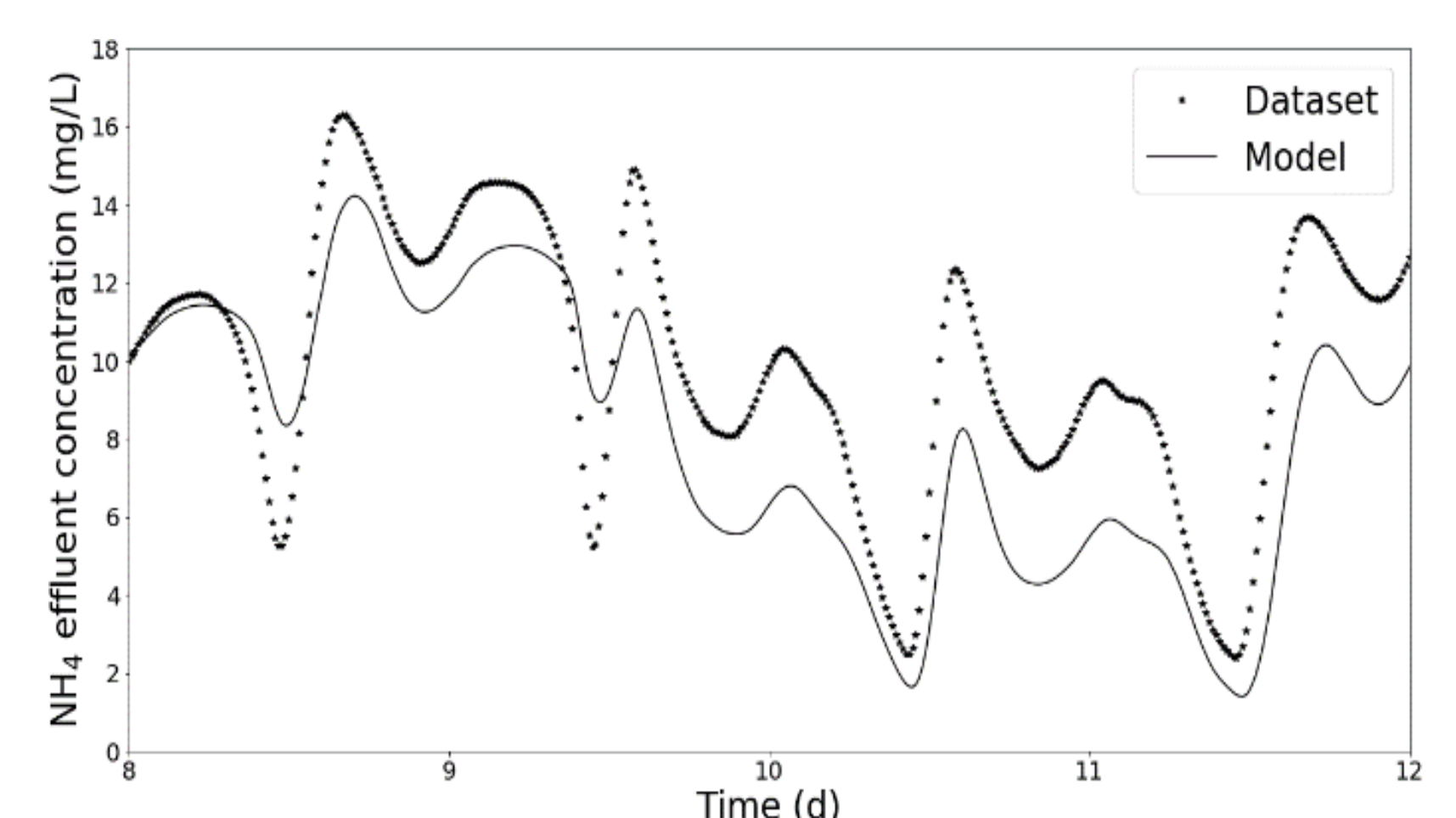
Simulation study

1. Generate data of 7 days of **dry weather** using BSM1
2. Train three models using this dataset
 - A **mechanistic** models with incomplete domain knowledge
 - A **data-driven** model
 - A **hybrid** model with incomplete domain knowledge

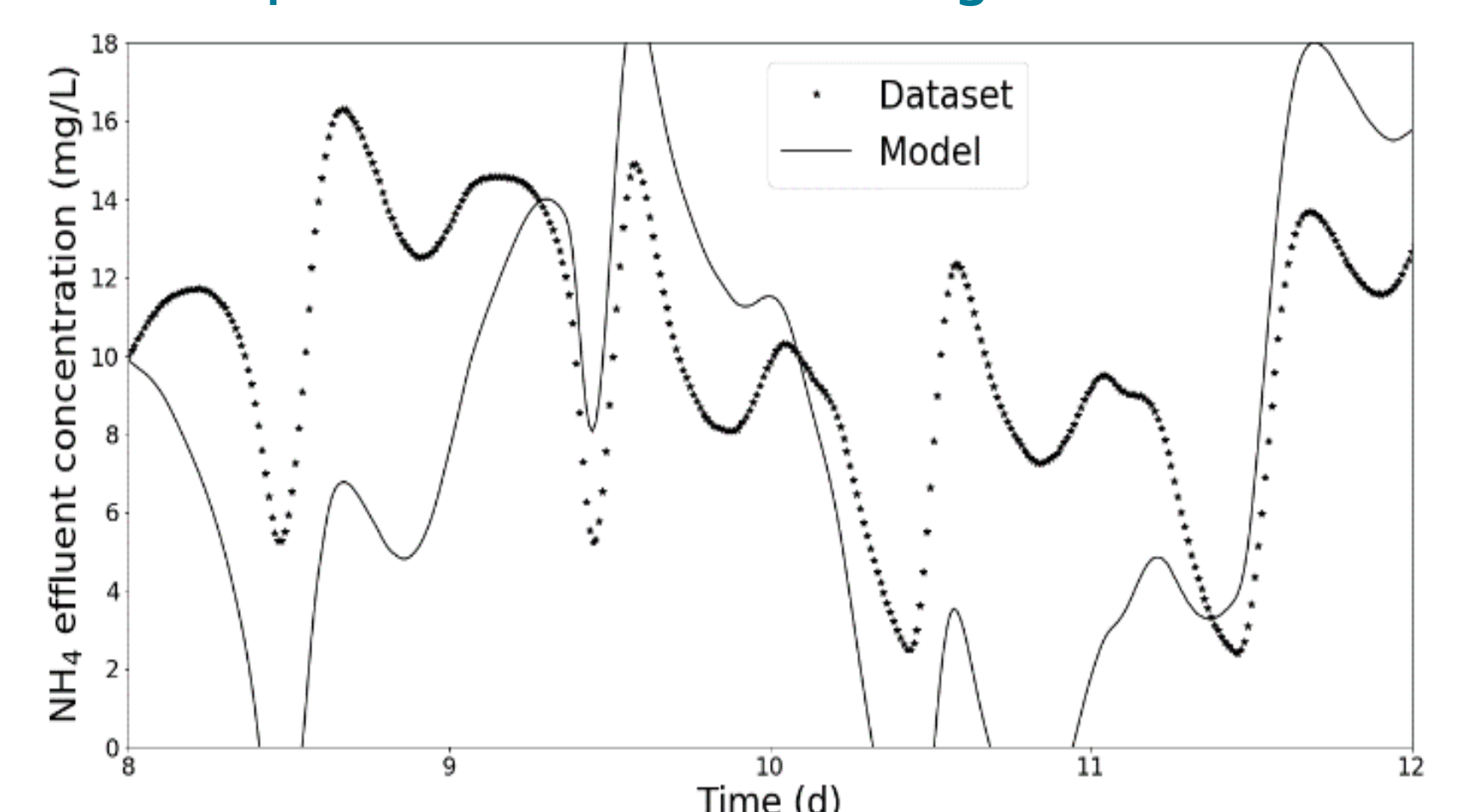
To simulate **incomplete domain knowledge**, the mechanistic (sub)models do not account for anoxic growth in heterotrophs

3. Simulate 7 days of **wet weather**

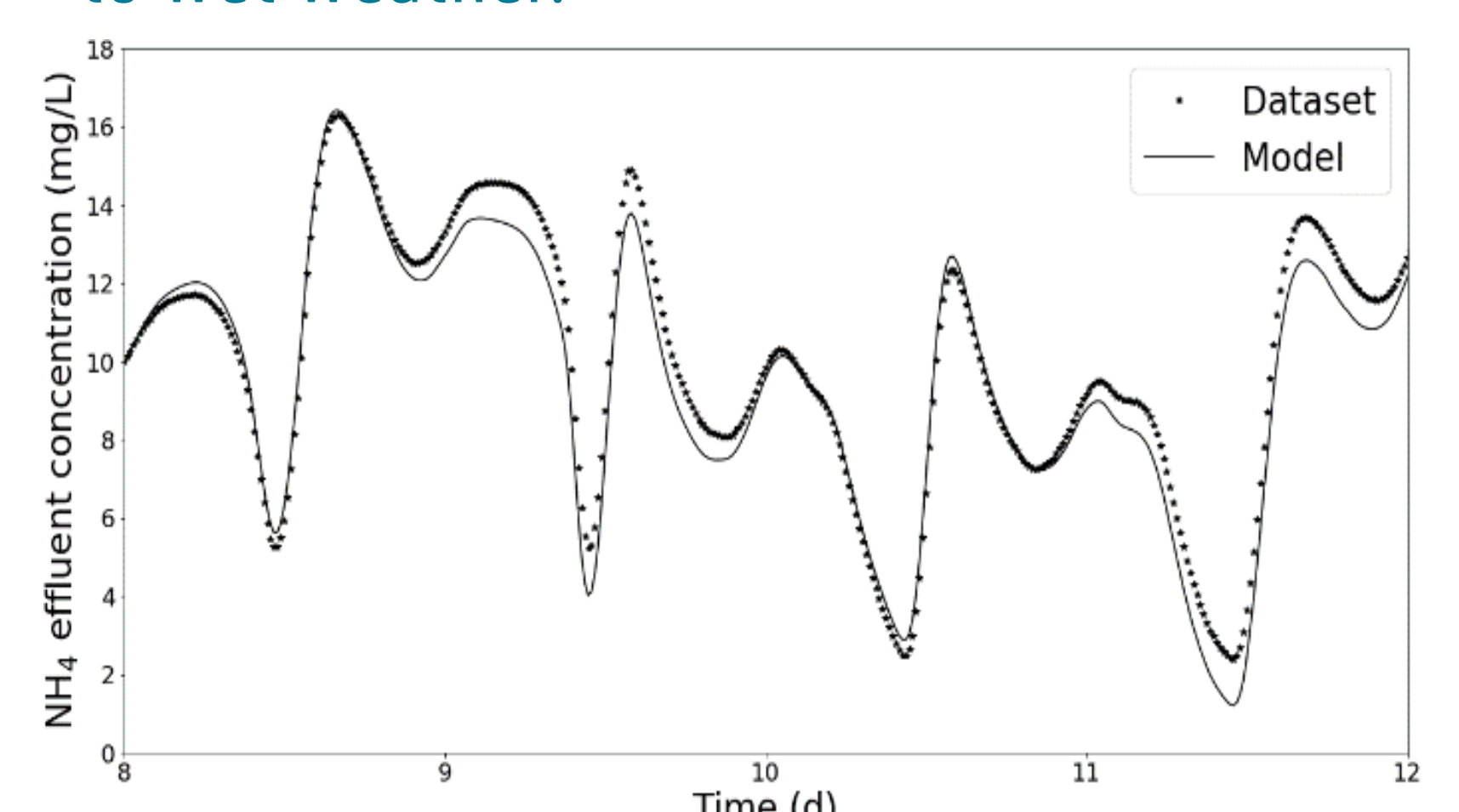
Results



The **mechanistic** model predicts the general trends, but **lacks accuracy** due to incomplete domain knowledge.



The **data-driven** model **fails to extrapolate** to wet weather.



The **hybrid** model **accurately extrapolates** to wet weather.