

Soft sensing of intracellular states in bioprocessing with Ensemble Kalman Filters

18th international EnKF workshop (2023)
Norwegian Centre for Data Assimilation

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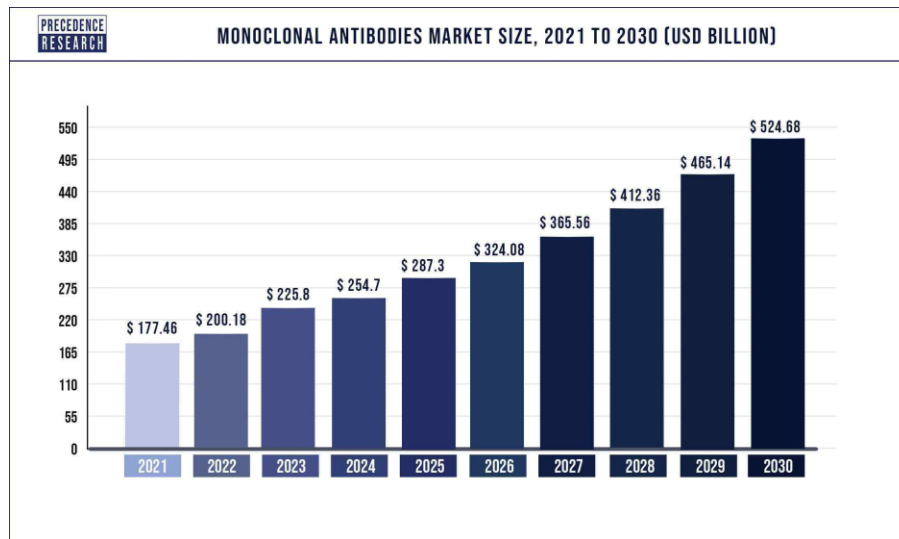
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Overview

- Introduction of biotherapeutics and bioprocessing
- Manufacturing challenges
- Technical challenge of accessing intracellular states
- Hybrid approach – motivation for using EnKF
- Design & Implementation of EnKF for soft sensing in bioprocessing

Background: Therapeutic proteins

- Biologically derived drugs
- The most common example is monoclonal antibody(mAb)
- Can be used to treat many diseases including cancer, autoimmune diseases, inflammatory diseases and infectious diseases, approved by US FDA
- Explosive market growth of mAb



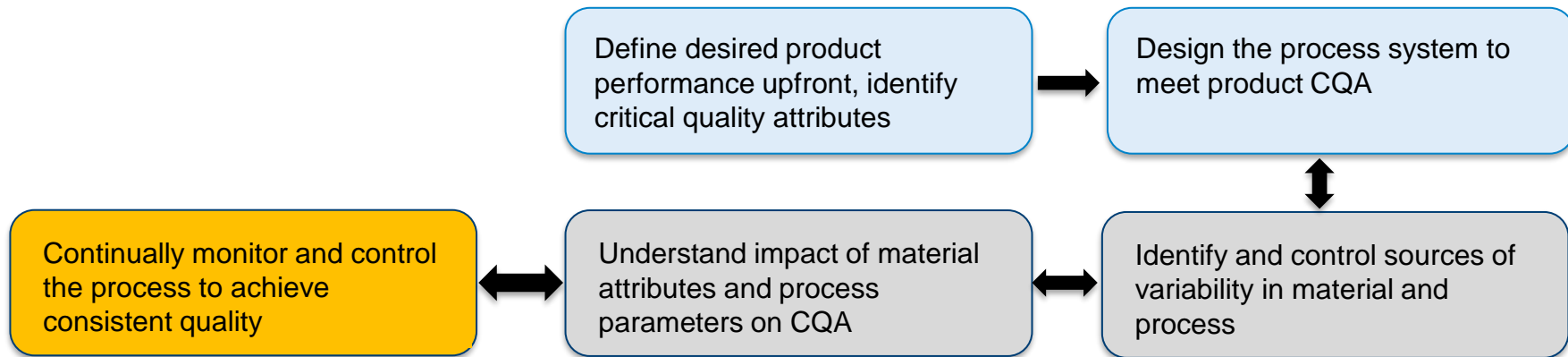
Bioprocessing of therapeutic proteins in mammalian cells

- Industrial production of therapeutic proteins, rely on living cells
- Mammalian cells are favoured due to compatibility to human bodies
- Nearly 70% of therapeutic proteins are produced in Chinese Hamster Ovary (CHO) cells.

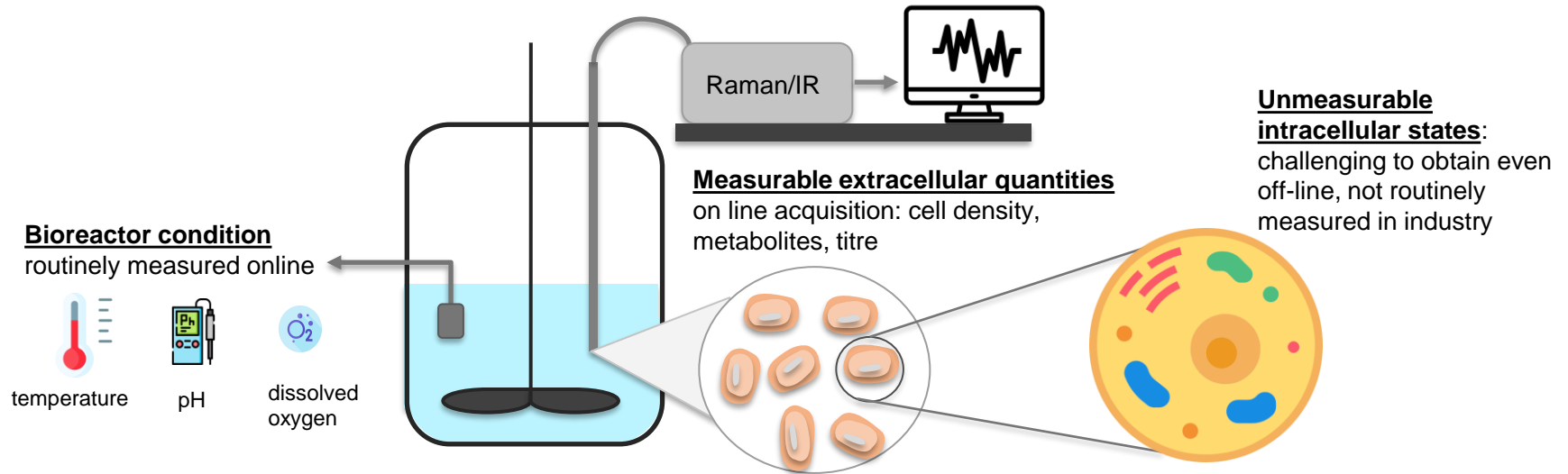
Manufacturing Challenges

- Low yield (but high demand)
- Biotic phase is a black box
- Lack of comprehensive Process Analytical Technologies
 - Limited online measurements
 - No intracellular information
- Poor controllability: Major problem in a highly regulated industry

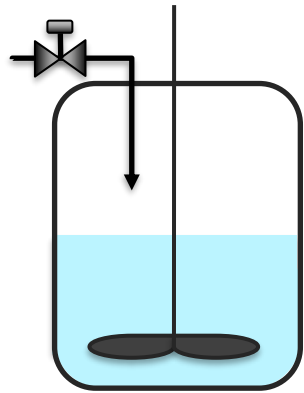
Product quality assurance - Quality by Design (QbD)



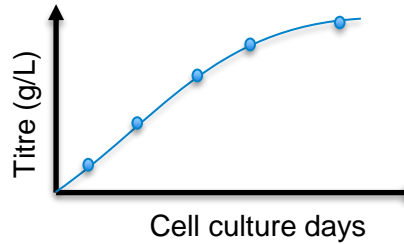
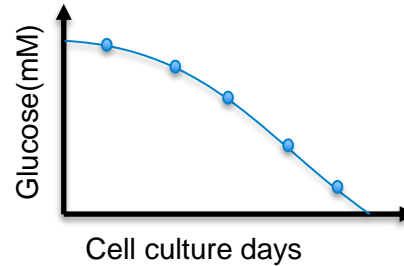
Online monitoring and control in bioprocessing



Mechanistic model development



Data Collection



Model Development

$$\mu = \mu_{max} \prod_{i=1}^{N.C.} \left(\frac{C_i}{K_{M,i} + C_i} \right)$$

$$q_i = \alpha_i \left(\frac{C_i}{K_{M,i} + C_i} \right)$$

$$q_p = \alpha_p \sum_{i=1}^{N.C.} \alpha_i q_i$$

Monod Kinetics

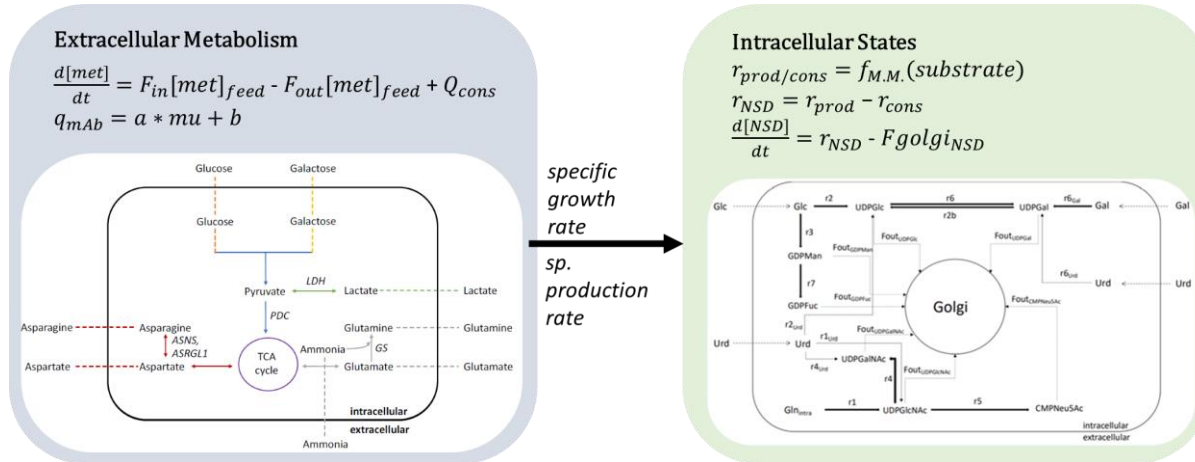
$$\frac{d(VX_V)}{dt} = \mu VX_V - Q_{out}X_V$$

$$\frac{d(VC_{i,in})}{dt} = Q_{in}C_{i,in} - Q_{out}C_i + q_i VX_V$$

$$\frac{d(VP)}{dt} = q_p VX_V - Q_{out}P$$

Material Balances

Previous Efforts – Mechanistic Models

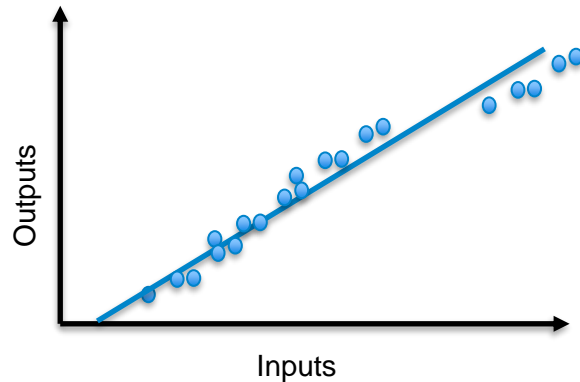


Challenges:

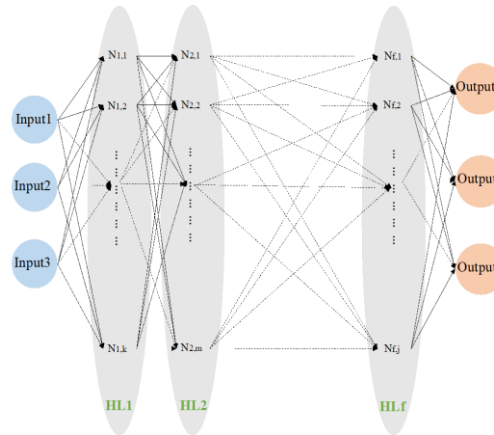
- Dynamic mechanistic models are highly specific to experimental conditions, cell line or product.
- Intracellular states are difficult to measure experimentally, therefore not routinely tracked.

Previous efforts: Data-driven models

Partial Least Squares



Artificial Neural Networks



Data Driven Approaches

- No need to reparametrize the model kinetic parameters
- Model trained with data, not specially designed for the system

However,

- Large dataset required
- No system understanding embedded within the model

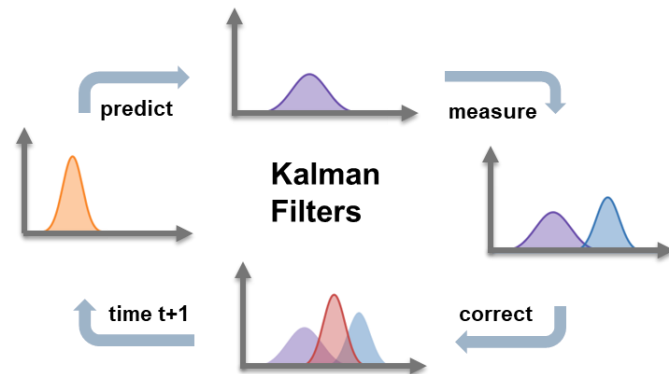
Ensemble Kalman Filter (EnKF) as soft sensor

Takes benefits from both mechanistic models and data-driven models for estimation of unmeasurable intracellular states

- Contains biological information, troubleshoot and inform process decisions
- Avoid reparameterization of kinetic parameters
- More flexible in adapting into different conditions without a large dataset, not bound to fixed parameters

Data Assimilation: Ensemble Kalman Filtering (EnKF)

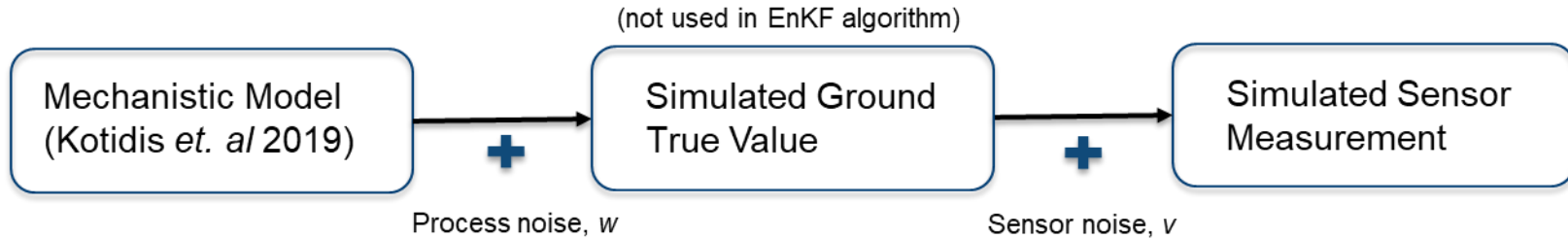
- State estimation for unmeasurable intracellular states by model inference through extracellular metabolites



Experimental Setup

- A fed-batch CHO cell culture process producing an IgG antibody
- Control experiment: Glucose and amino acid nutrients added every two days
- Feeding experiment (10G5U): Additional 10mM galactose and 5mM uridine fed on Day 4 and Day 8
 - in order to change the quality profile of the product
- Daily measurements were taken for relevant extracellular metabolites and intracellular states

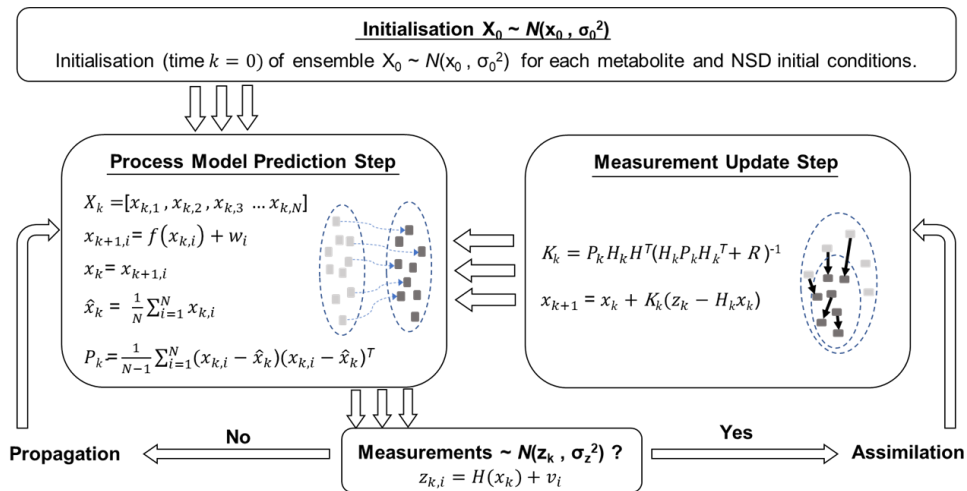
Data Augmentation



Ensemble Kalman Filter (EnKF) Algorithm

Notations:

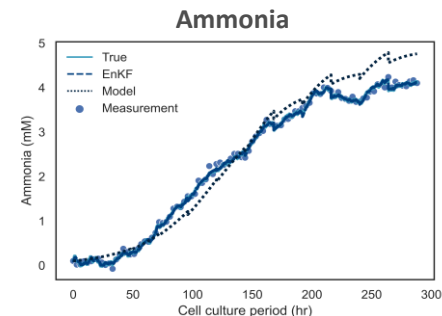
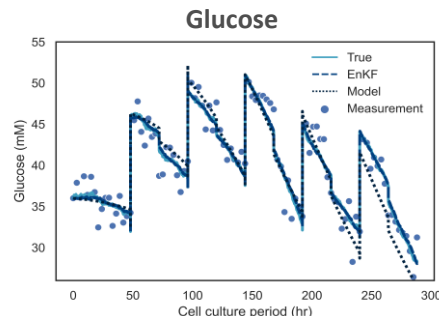
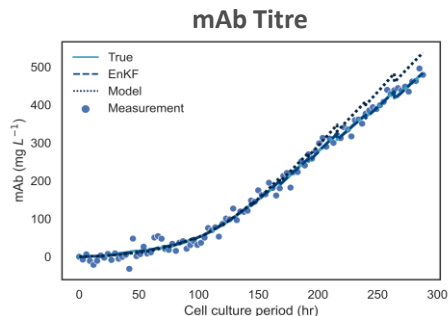
- X , sampled ensemble;
- x , process states;
- f , process model;
- w , white Gaussian noise of process;
- P , state covariance;
- K , Kalman gain;
- H , measurement function;
- R , measurement noise covariance;
- z , measurement;
- v , white Gaussian noise of measurement



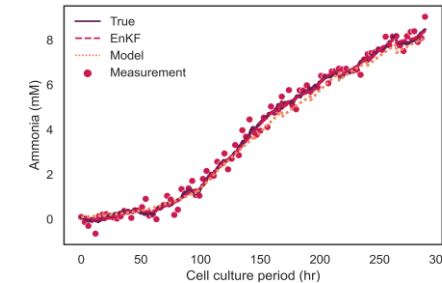
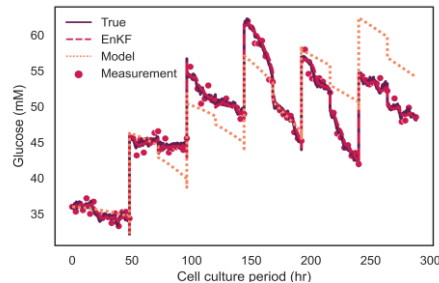
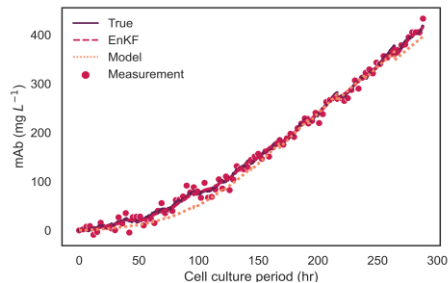
- EnKF iteratively updating the forecast as new information becomes available

Results 1 Extracellular Metabolites

Control Experiment,
NO ADDITIONAL FEEDING

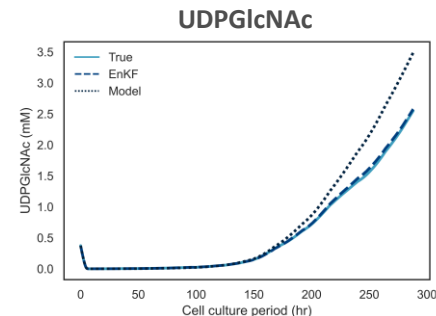
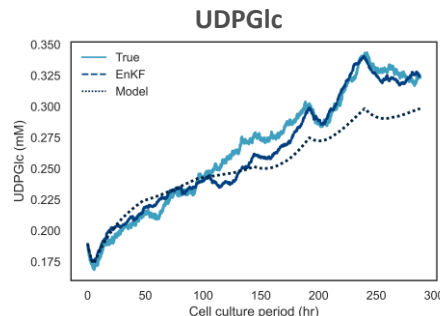
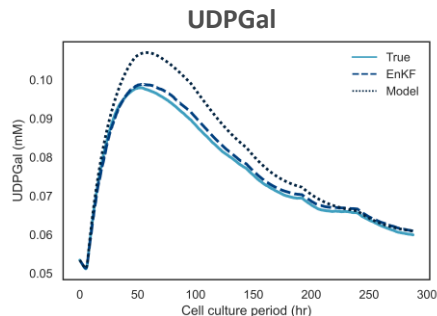


10mM GAL & 5mM URD
FED ON DAY 4 and 8

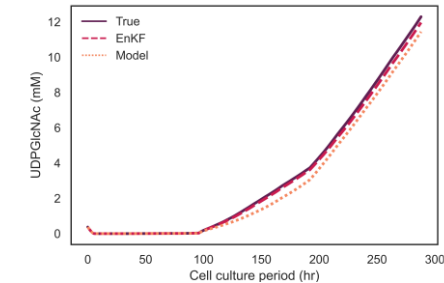
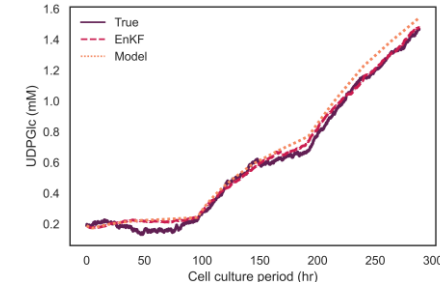
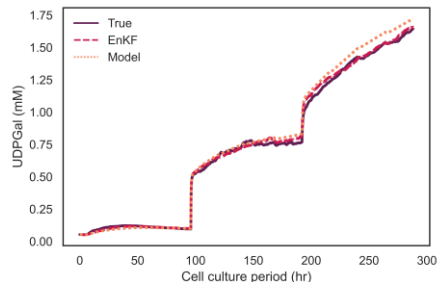


Results 2 Intracellular States

Control Experiment,
NO ADDITIONAL FEEDING

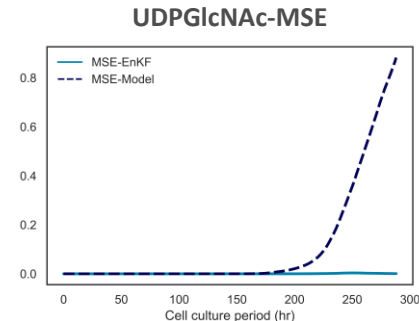
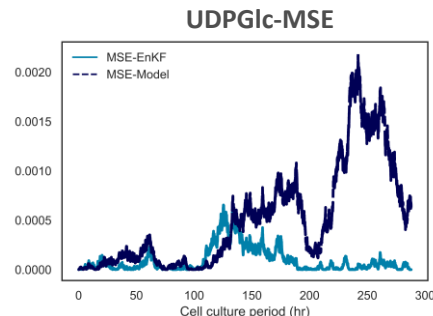
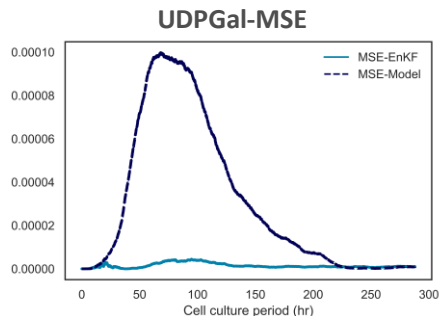


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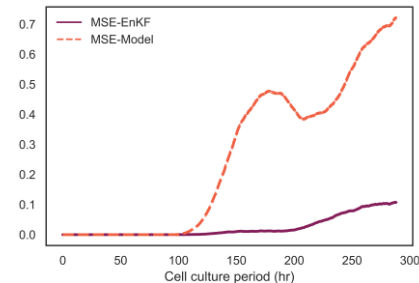
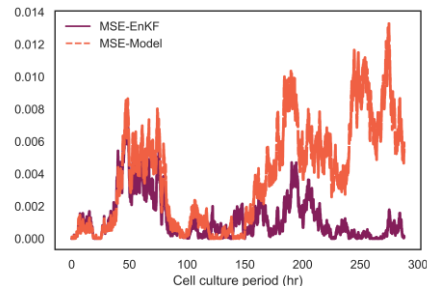
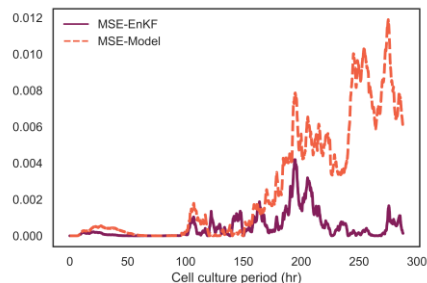


Results 2 MSE Comparison with True Values

Control Experiment,
NO ADDITIONAL FEEDING



10mM GAL & 5mM URD
FED ON DAY 4 and 8



Conclusion & Outlook

- EnKF takes advantages from both the mechanistic model and discrete sensor observations
- EnKF reduces the sensor noise for measurable extracellular metabolites
- EnKF as soft sensor for estimating unmeasurable intracellular states, which can be used to ensure product quality during manufacturing
- Enables more informed process control strategies
- Experimental validation
- Potentially transfer the framework to other process conditions, cell line or product

Thank you