

Predictive Power: Accelerating Bioreactor Process Development with Hybrid Models

June 26th, 2025

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Hybrid model definition

- Hybrid models combine 2 or more models together (i.e. Mechanistic + Machine Learning)

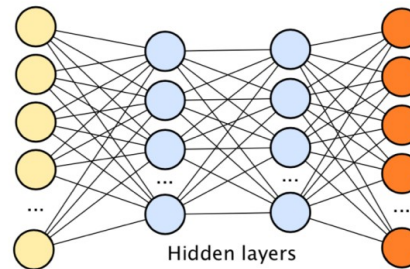
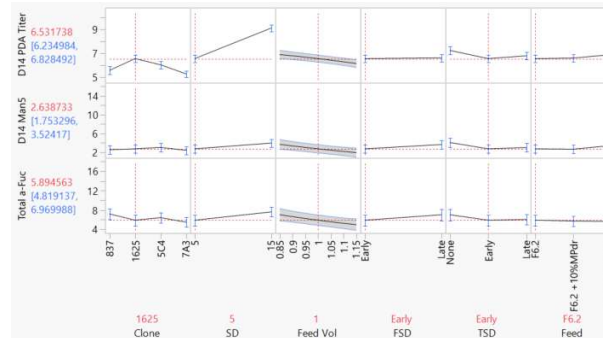
Mechanistic

- Understanding of mass balances
- Monod equation (cell growth)
- Flux balance / metabolic flux analysis (metabolites, product)

$$\begin{aligned}
 \frac{dVCD}{dt} &= \mu \cdot VCD - F_b \cdot VCD \\
 \frac{dGlc}{dt} &= q_{glc} \cdot VCD - (F_b + F_p) \cdot Glc + F \cdot Glc_f \\
 \frac{dGln}{dt} &= q_{gln} \cdot VCD - (F_b + F_p) \cdot Gln \\
 \frac{dGlu}{dt} &= q_{glu} \cdot VCD - (F_b + F_p) \cdot Glu \\
 \frac{dLac}{dt} &= q_{lac} \cdot VCD - (F_b + F_p) \cdot Lac \\
 \frac{dNH_4}{dt} &= q_{NH_4} \cdot VCD - (F_b + F_p) \cdot NH_4 \\
 \frac{dTiter}{dt} &= q_{titer} \cdot VCD - (F_b + F_p) \cdot Titer
 \end{aligned}$$

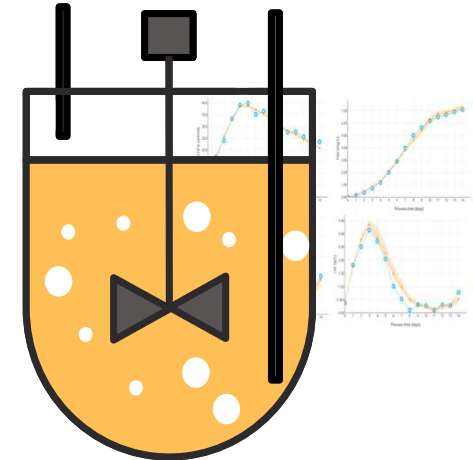
Machine Learning

- PLS regression
- DoE / LHD design



Hybrid

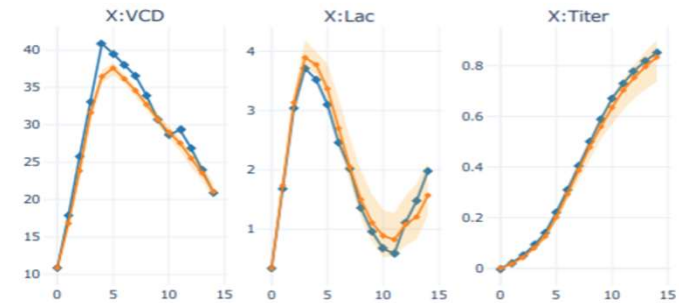
- Digital representation of the production bioreactor
- Simulate bioreactor performance



Collaboration History

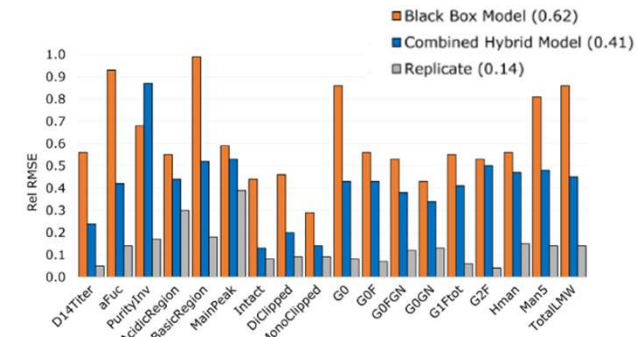
• Project 1 - Establish Model Capabilities

- Goal: Evaluate the Bioreactor Propagation Model
- Outcome: Propagation models can replicate physical systems



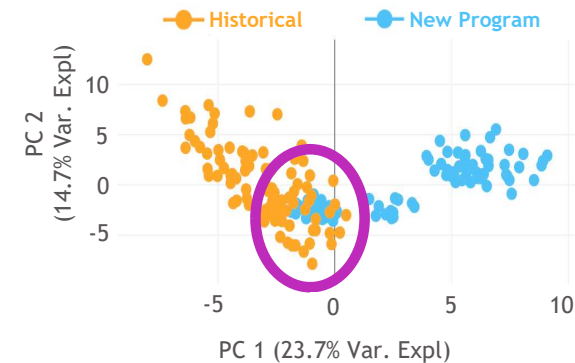
• Project 2 - Product Quality Prediction

- Goal: Evaluate specific objectives including product quality prediction and compare against hybrid modeling alternatives
- Outcome: Yes, quality can be predicted with hybrid model and are superior to black box models (focus area of this talk)

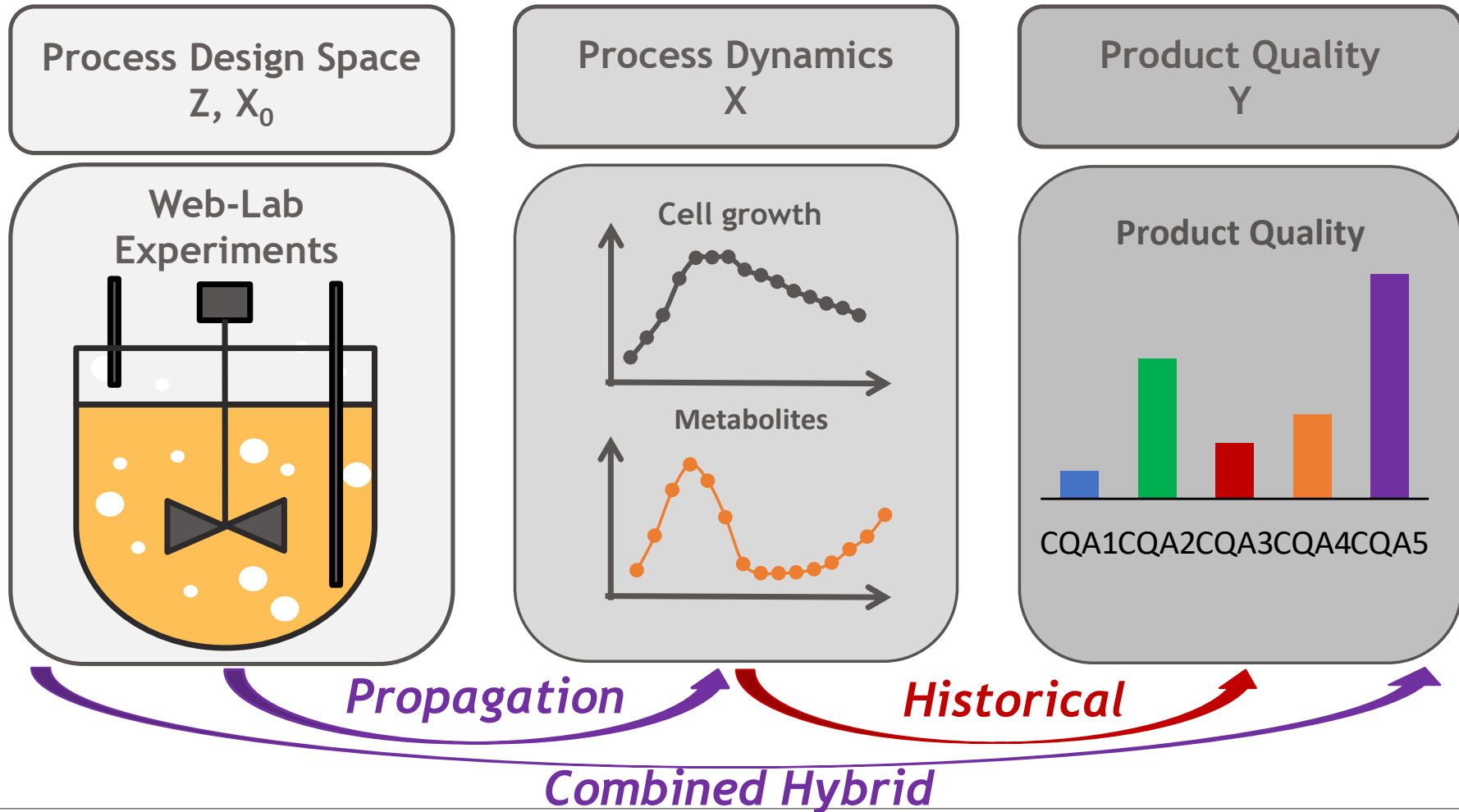


• Project 3 - Knowledge Transfer Across Clones, Scales, and Programs

- Goal: Evaluate how training data from one source can be used to support another application
- Outcome: Yes, knowledge can be transferred between applications (focus area of this talk)



Production bioreactor hybrid models can predict process dynamics *and* product quality from initial conditions



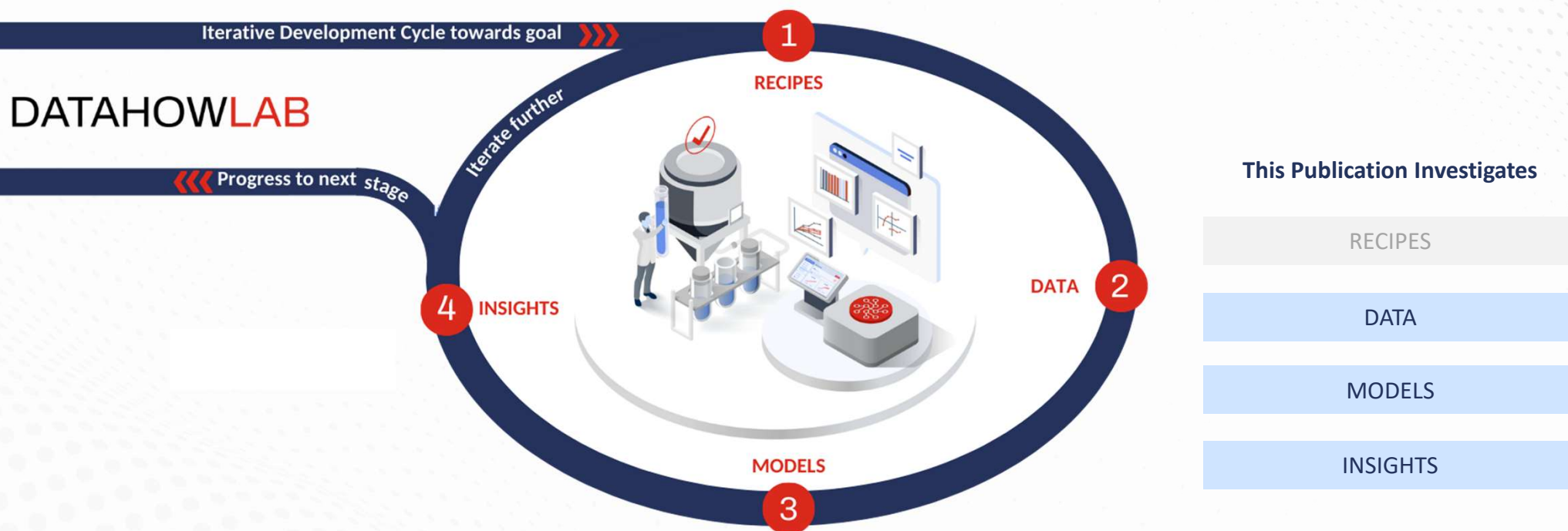


Case Study: Hybrid Modelling vs Industry Standard

An innovative hybrid modelling approach for simultaneous prediction of cell culture process dynamics and production quality.

DataHow Methodology for Model-Based Process Design Workflow

Hybrid Modelling vs Industry Standard



Hybrid Models vs. Industry Standard

Understanding & Predicting CQAs

Case Study 1

Hybrid Models

mAbs



The **Project**:

Evaluate the ability of hybrid process models to accurately predict CQAs compared to industry state-of-the-art “black box” models.

The **Challenge**:

48 (5 liter scale) experiments were designed and conducted by BMS to evaluate the impact of **12 process parameters** on **18 product CQAs**.

The **Objectives**:

1. Evaluate ability of hybrid models to predict CQAs
2. Assess how much experimental data is needed to accurately predict CQA's for each approach
3. Assess other benefits of Hybrid Models for Process characterization

Hybrid Models vs Industry Standard

Closer Look at Experimental Data

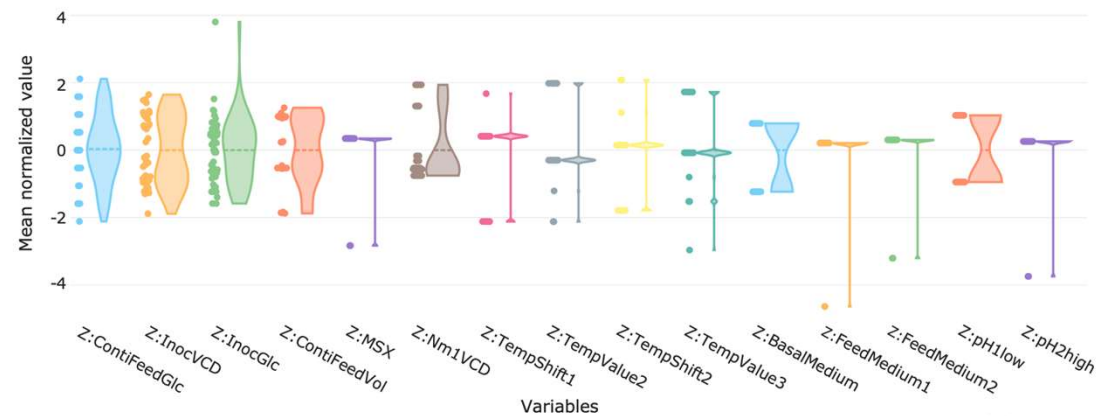
2

Data

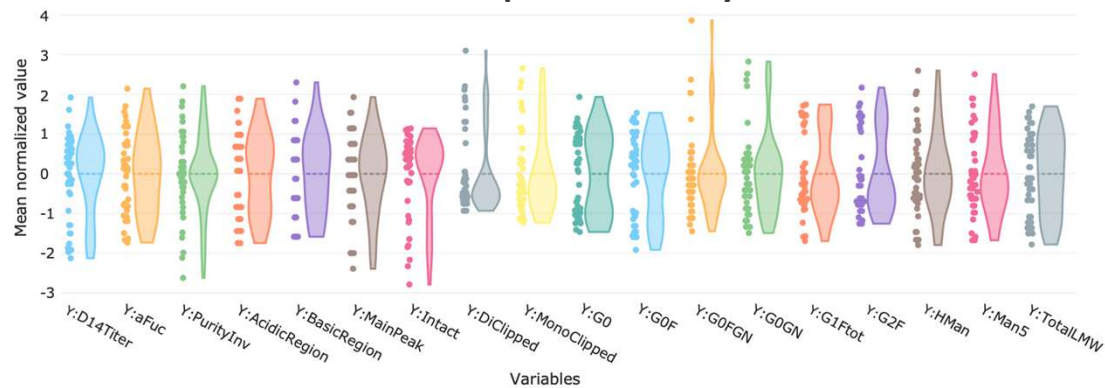
Design of Experiments

DoE	Batches	Studied parameters
DoE 1	12 × 5L	MSX levels in seed train, Temperature shift, Feed medium, Feed volume
DoE 2	12 × 5L	Inoculation density, Temperature shift, pH setting, Feed volume
DoE 3	12 × 5L	MSX levels in seed train, Basal medium, Feed medium, Temperature shifts
DoE 4	12 × 5L	Inoculation density, Basal medium, Feed medium, Feed volume

Inputs Variability



Outputs Variability



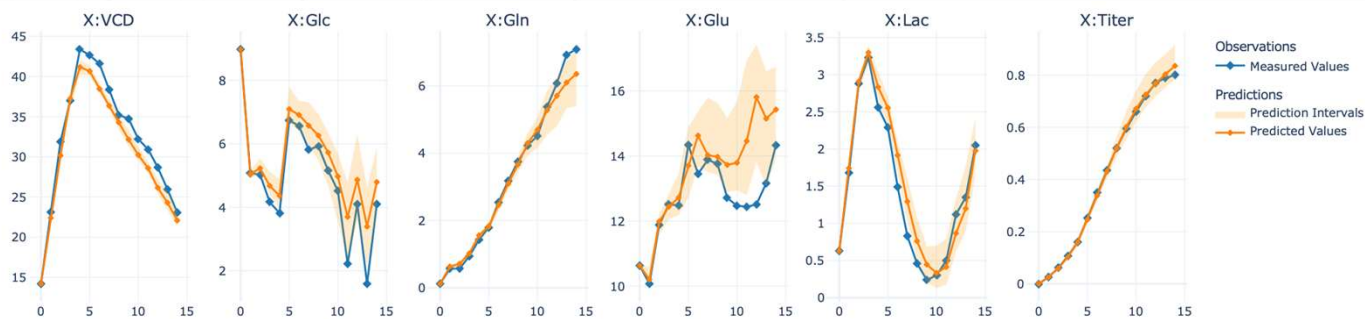
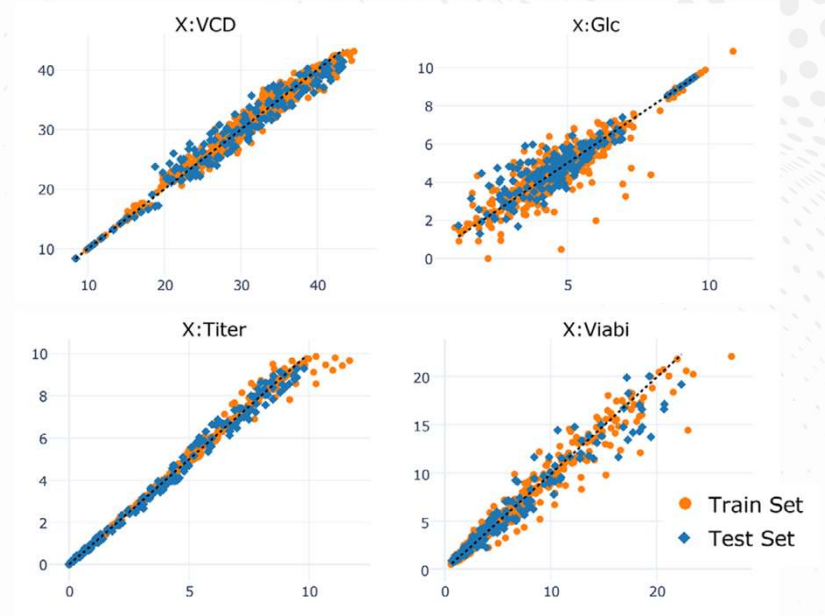
Hybrid Models vs Industry Standard

The Performance of Hybrid Model

Propagation Model

- A discrete hybrid model with a Gaussian Processes was used to characterize the time evolution of the X variables.
- The model propagates the state of the bioreactor adjusted for mass balance equations by predicting the rate of change of the measured metabolites

$$c(t_{i+1}) \approx c(t_i) + \left(GP(s) \cdot V + u_f - c(t_i) \cdot \frac{dV}{dt} \right) \cdot \frac{t_{i+1} - t_i}{V}$$



Hybrid Models vs Industry Standard

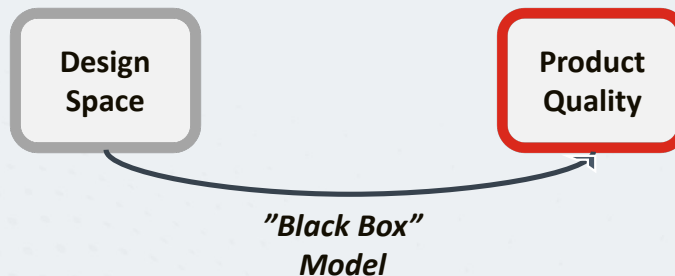
The difference in utilized information between the Approaches

3

Models

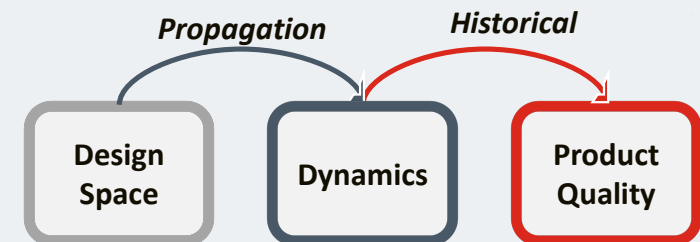
Industry Standard Response Surface Model

- Utilizing simple linear regression approach to model directly the product quality attributes by using only the designed conditions. It doesn't consider process dynamics.



Combined Hybrid Model

- The combination of Propagation Model and Historical Model, allows to directly link the final properties of the process and the product CQAs to the manipulated process parameters

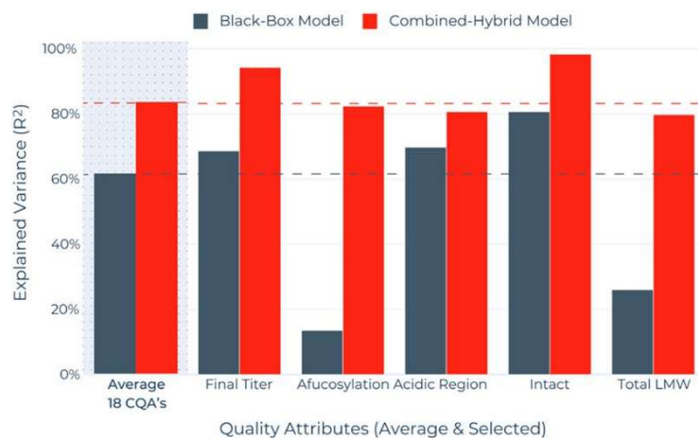


Hybrid Models vs Industry Standard

The Performance of Combined Hybrid Model Compared to "Black Box" Response Surface Model

3 Models

Understanding & Predicting CQAs: Black Box vs Hybrid



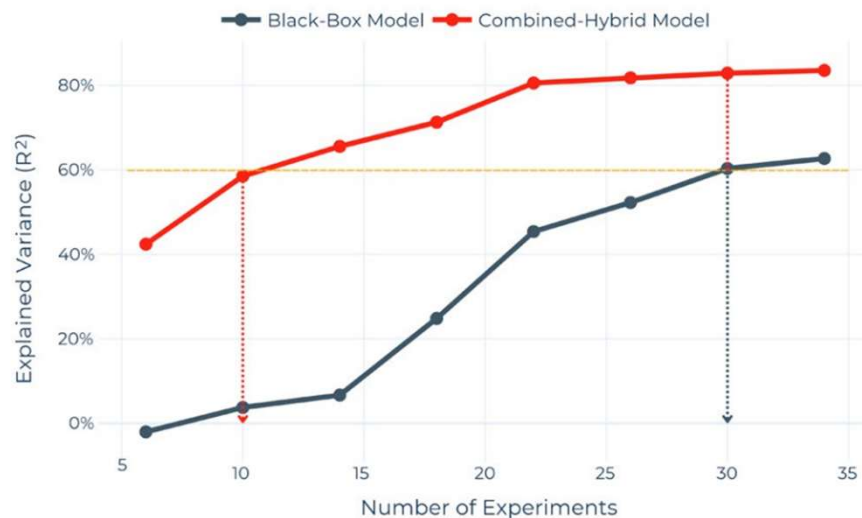
↑ 22%

- On average, hybrid models explained **CQA variance +22%** better than black box
- Even after 34 experiments, black-box models were unable to reliably predict 5 of the 18 CQAs (highlighted: Afucosylation / Total LMW)
- For some CQAs, the predictive ability of hybrid models was approaching 100% (highlighted: Titer / Intact)

Hybrid Models vs Industry Standard

Model Insights with fewer performed experiments

of Experiments required to predict CQAs: Black Box vs Hybrid



- Black box models needed **30 experiments** before they could understand the CQA / process parameter interrelationships and reliably predict CQA values
- Hybrid models only required **10 experiments** to reach the same level of predictive accuracy

↓ 3x

Fewer experiments

4

Insights

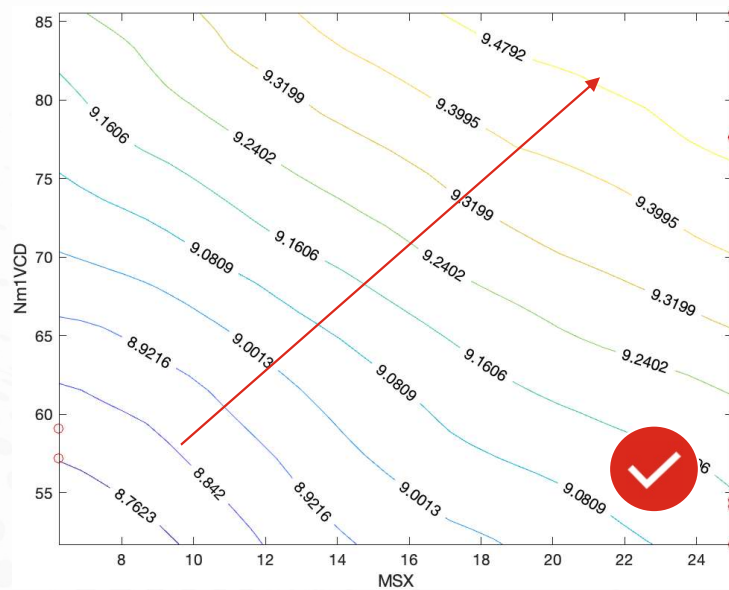
Hybrid Models vs Industry Standard

Models and analytics supporting development objectives towards process characterization

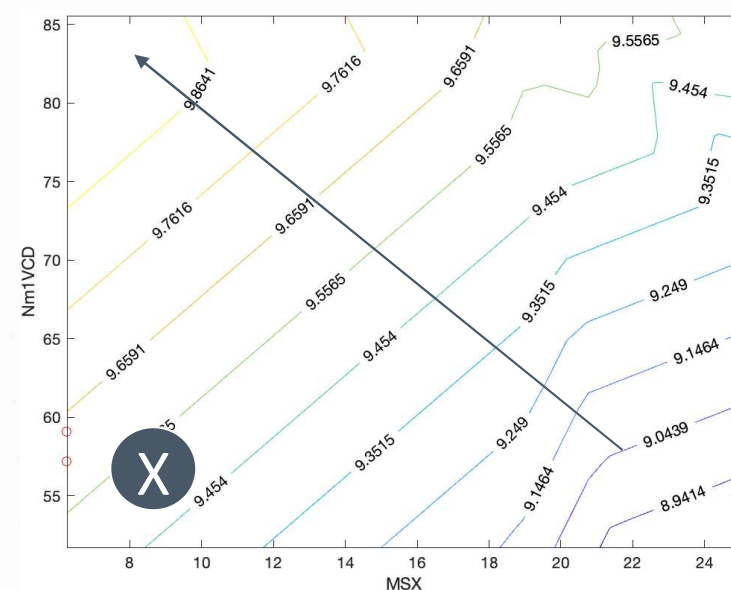
Exploring the design space with:

- **Hybrid models** accurately understood the complex interrelationships to suggest areas of further exploration
- **Black Box** models struggle to understand complex dynamics. They suggest further exploration in the wrong direction

Hybrid Models



Black Box Models



4

Insights



Case Study: Influence of Design of Experiments on Modelling Approaches

26 June 2025, Jakub Polak

DataHow Methodology for Model-Based Process Design Workflow

Influence of Design of Experiments on Modelling Approaches



Influence of Design of Experiments on Modelling

Understanding & Predicting CQAs



The Project:

Compare classical **Full factorial design** (FFD) to **latin hypercube design** (LHD) for different modelling approaches such as **response surface model** (BBM) and **combined hybrid model** (CHM)

The Challenge:

112 (Tecan scale) experiments were designed and conducted by BMS to evaluate the impact of **10 process parameters** on 18 product CQAs. (with focus on Final Titer and Afucosylation)

The Objectives:

1. Which design allows to learn this behaviour most efficiently?
2. For which CQAs do we see the largest differences between different designs and model approaches?

Design of Experiments Options

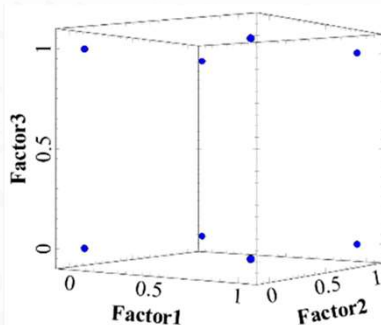
1

Recipes

Full Factorial Design (FFD)

FFD is optimal for linear models and requires a large number of experiments as a function of the number of variables (factors)

A 2-level FFD with 9 factors has been designed. This corresponds to a resolution 4 design (all main factors are not confounded) with 32 experiments. Each design on these two levels is also a resolution 4 design.

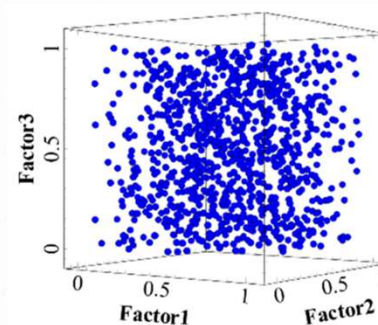


FFD
32 exp

Space Filling Design (LHD)

LHD is optimal for ML algorithms, as it uniformly maps the space of the parameters, thus allowing ML to learn higher-order dependencies.

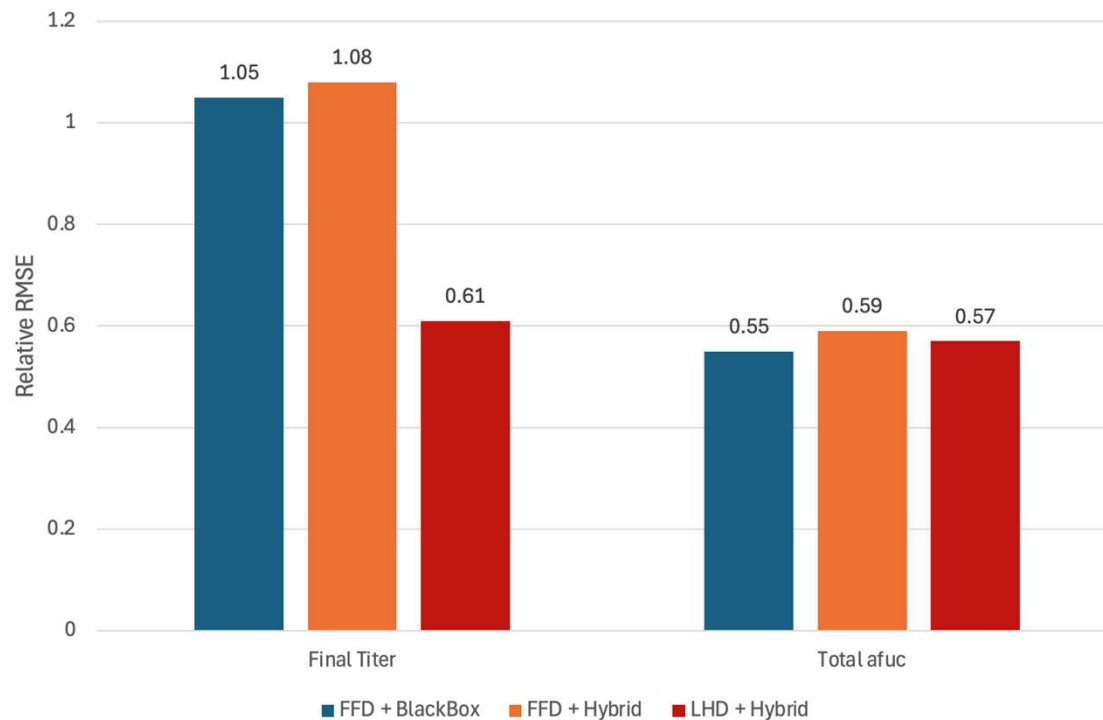
Two nested LHD's were designed, each with 24 experiments using 10 factors. This will allow us to simulate the effect of a second round of experiments to refine the original model, where the entire space is re-mapped (or the LHD is augmented).



LHD
24 exp

Influence of Design on Modelling Approaches

A stark comparison between different values.



- For Final Titer, the **Combined Hybrid model trained on LHD experiments delivers the best results** while the FFD design is not sufficient to learn the behavior
- For Total afuc, the model performances **are similar across the different models and designs** used.

3

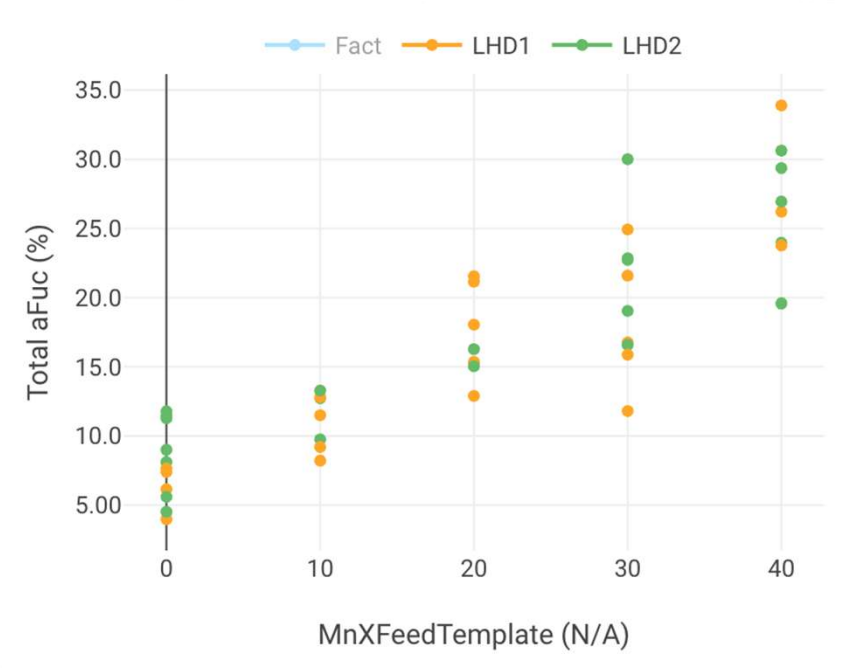
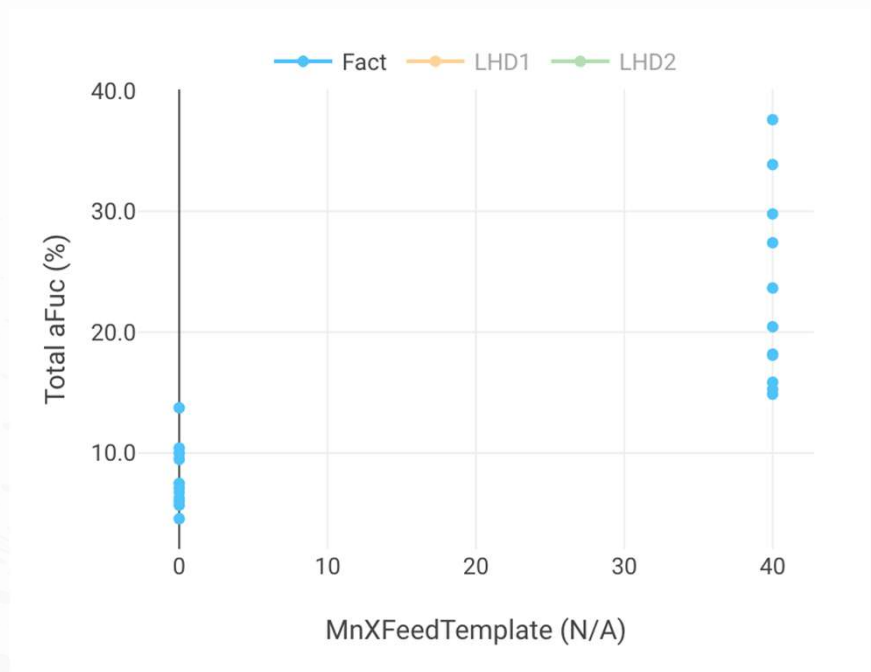
Models

Why FFD Design and BlackBox Model is Sufficient

When the response variable has clear linear dependence.

2

Data

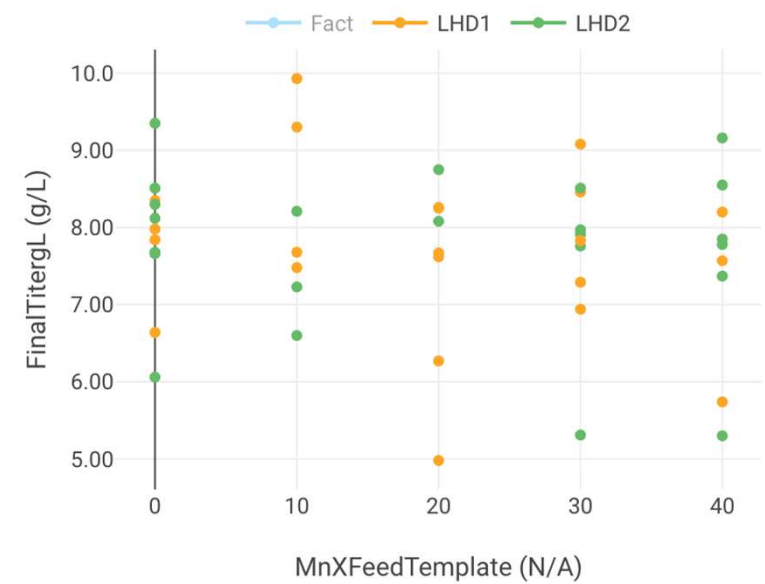
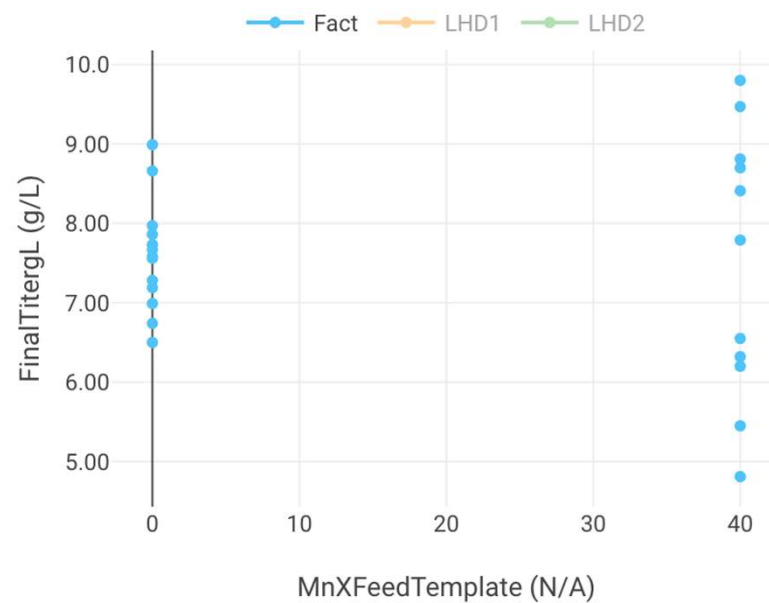


Why FFD Design and BlackBox Model is **NOT** Sufficient

When the response variable doesn't have linear dependence.

2

Data

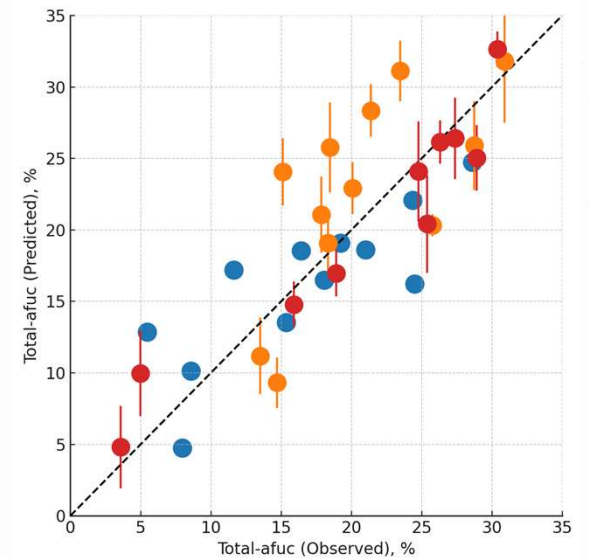
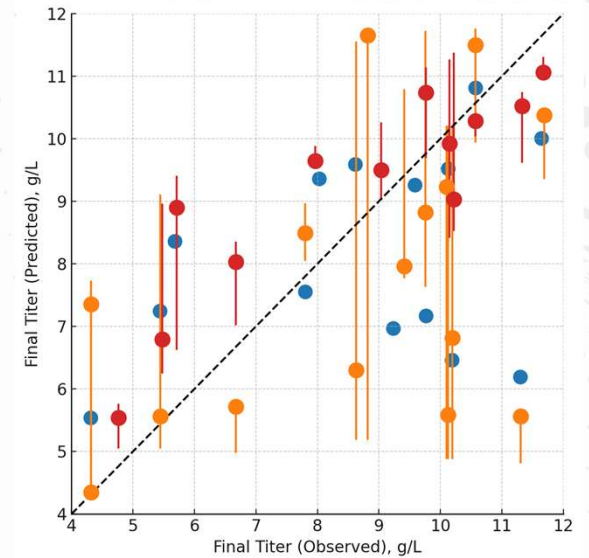
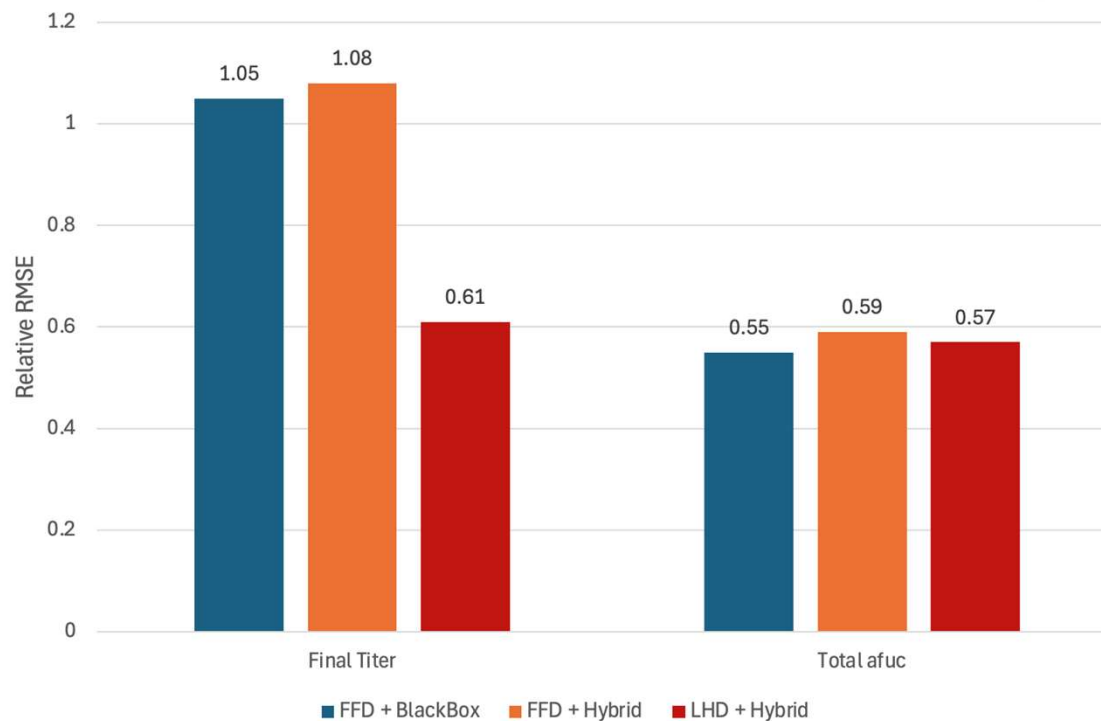


Influence of Design on Modelling Approaches

A closer look into model performance in parity plots.

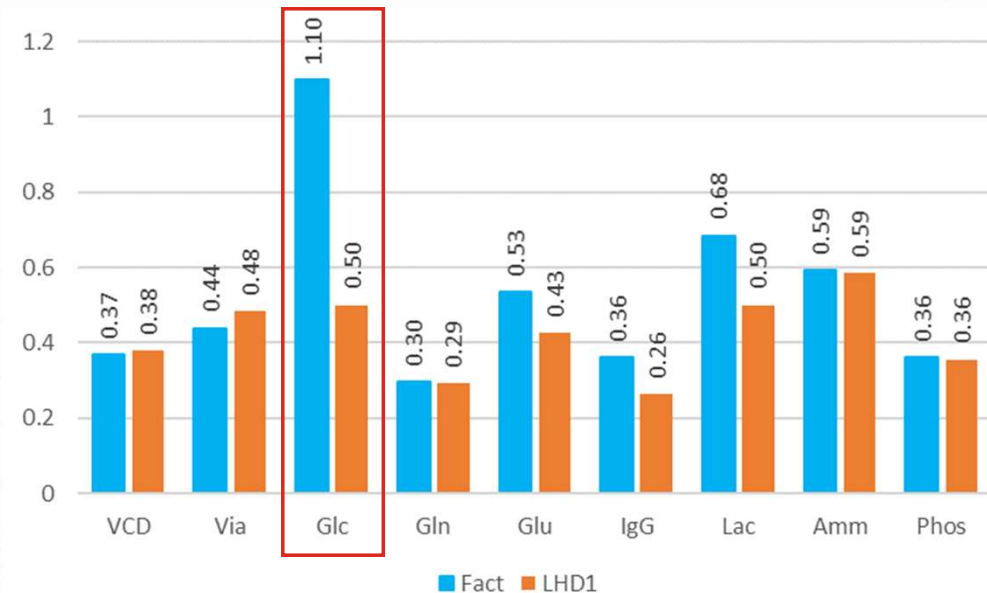
3

Models



Insights on the predictions from the model

Variable importances from the model of quality attributes. What does the model sees?



- The propagation models are integral to the Combined Hybrid Model. LHD design demonstrates superior performance.
- Specifically, for Glc, when the model is trained on the FFD, certain experiments are inaccurately predicted, including the VCD.

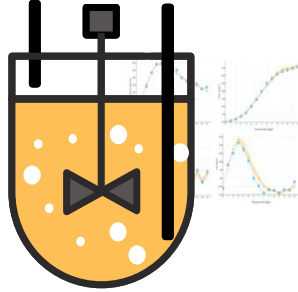
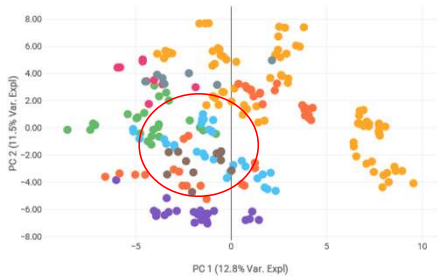
4

Insights

North Star Vision for Hybrid Modeling in Cell Culture

Model-First
Commercial PD

Biologics Development



Goal: Reduce **timelines** of highly **productive** and **robust** process development

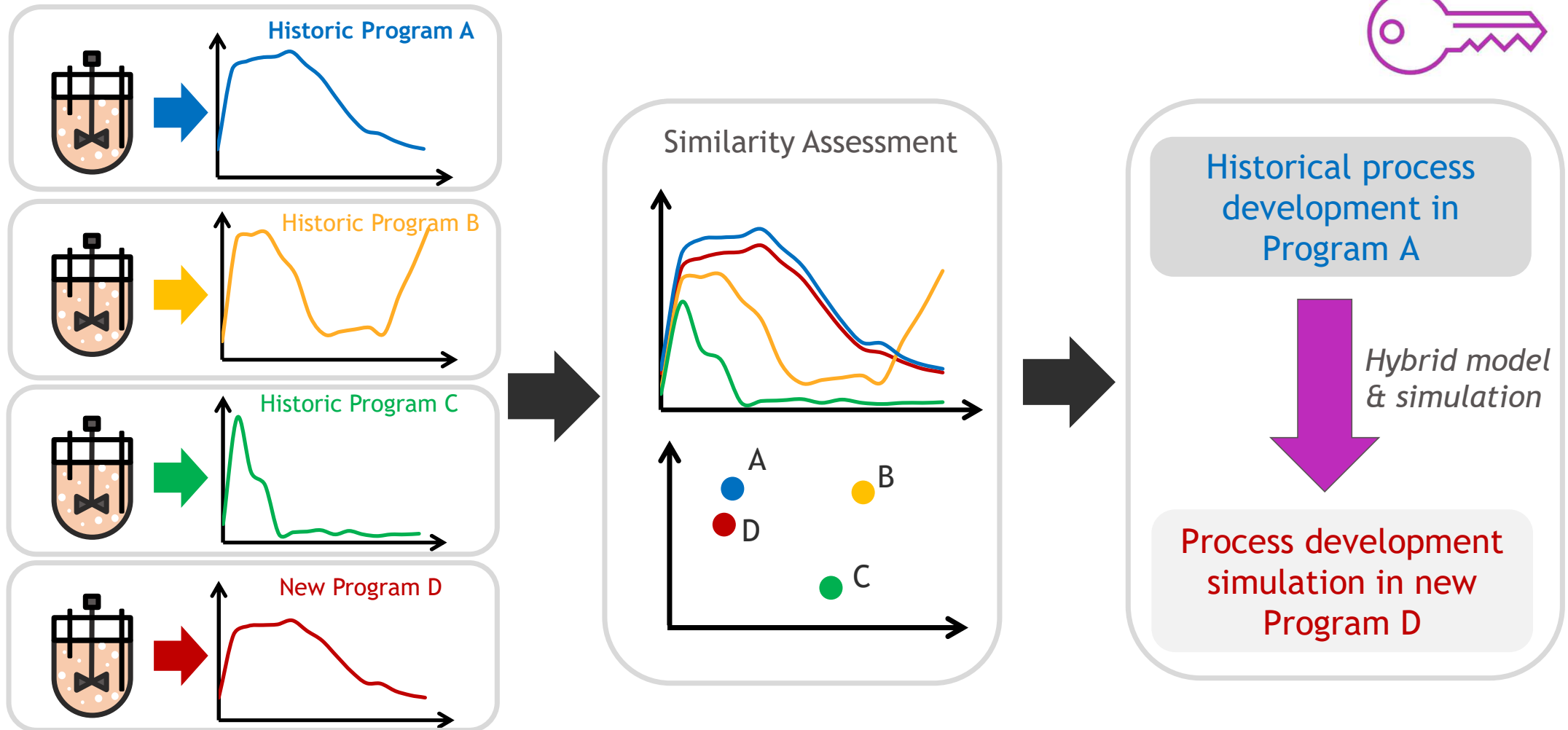
Case Study 1:

Model-First Approach to Process Development

(Knowledge Transfer Across Programs)

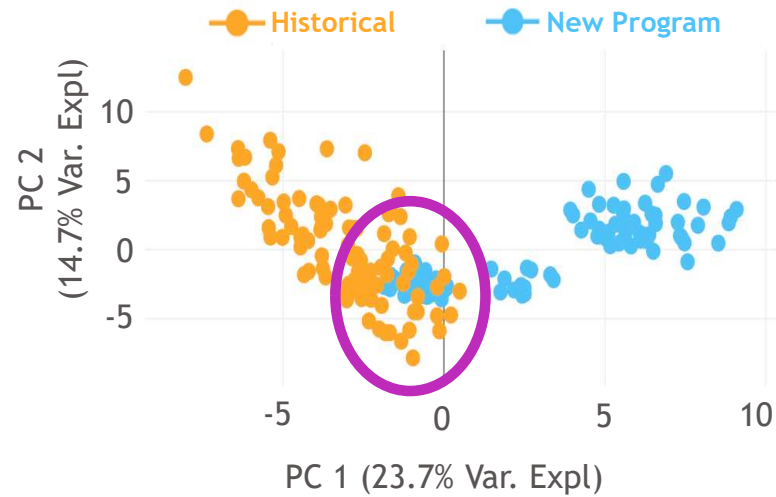
Case Study Credit: Zhuangrong Huang

Knowledge transfer is key to enable model-first in process development



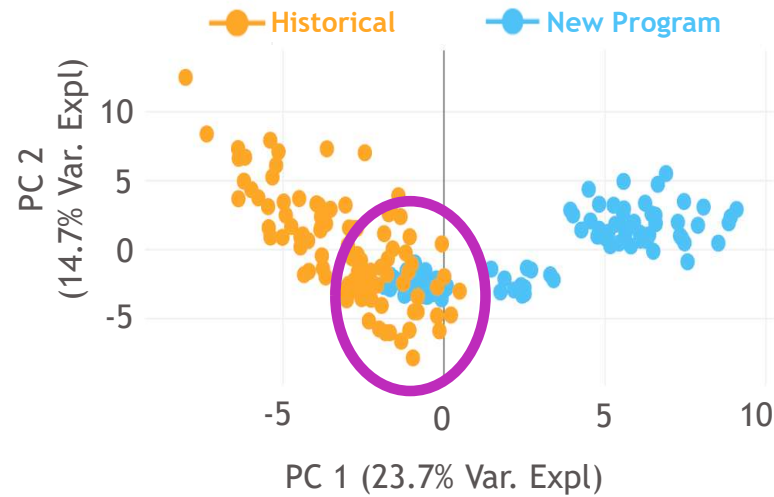
Knowledge transfer is key to enable model-first in process development

Similarity Assessment

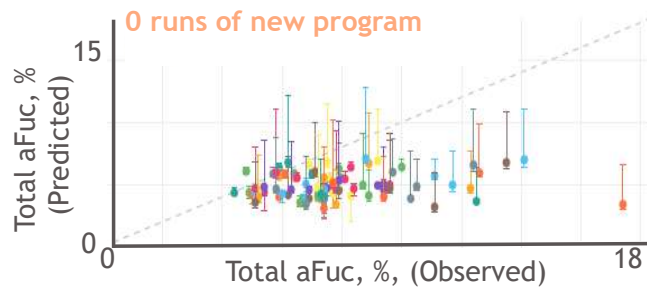
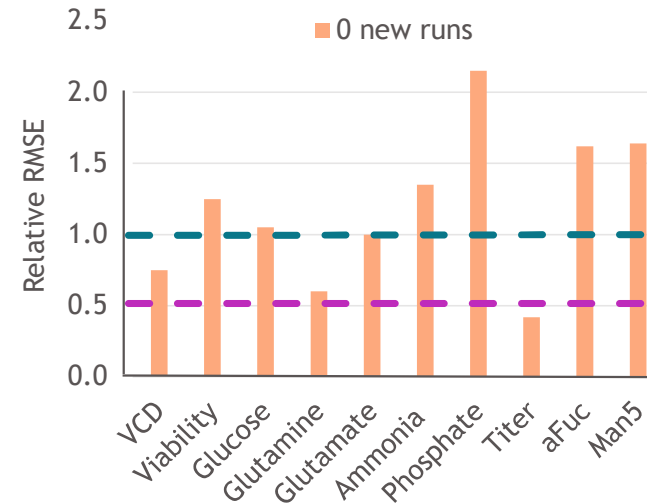


Knowledge transfer is key to enable model-first in process development

Similarity Assessment

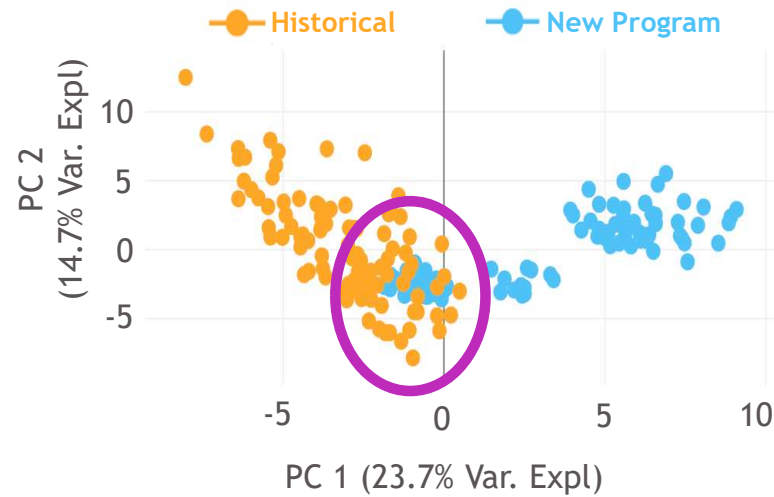


Model Error

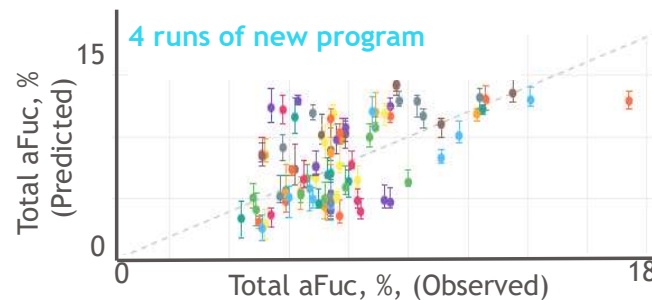
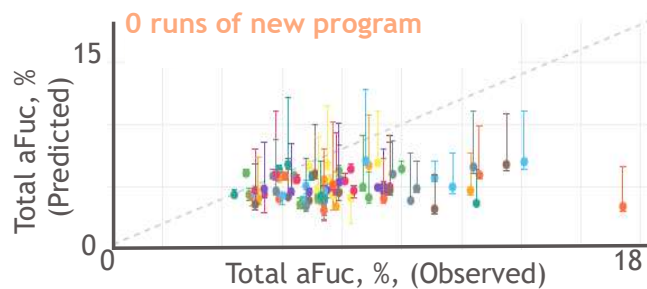
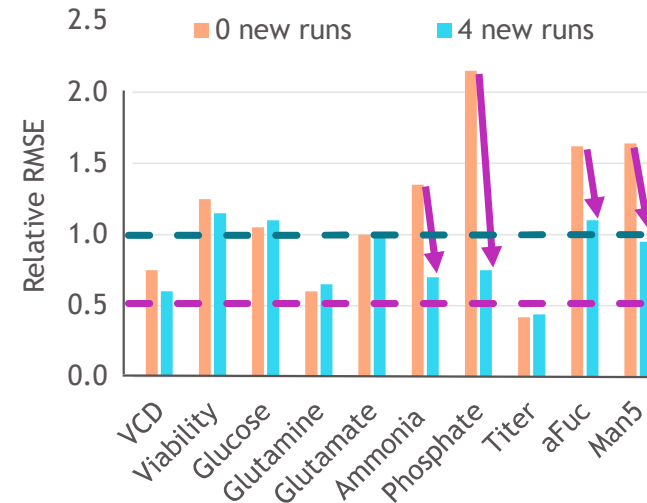


Knowledge transfer is key to enable model-first in process development

Similarity Assessment

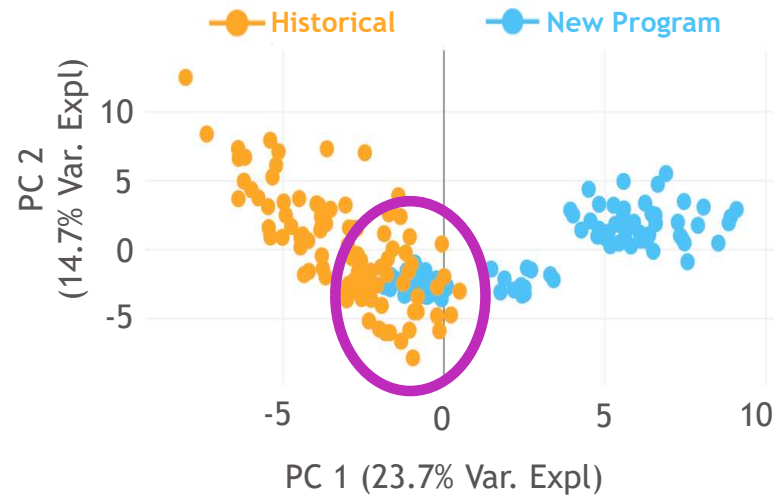


Model Error

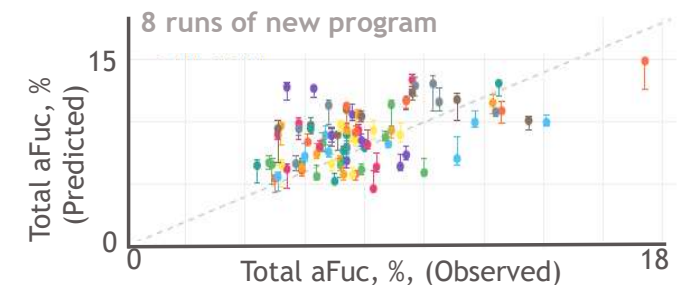
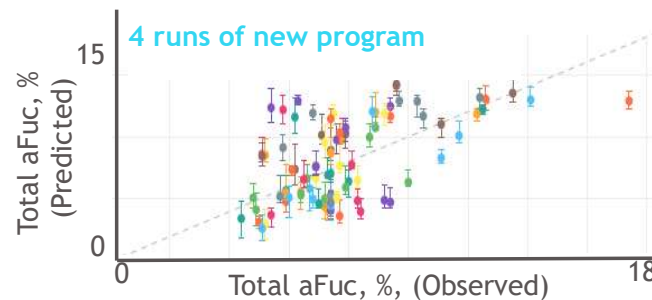
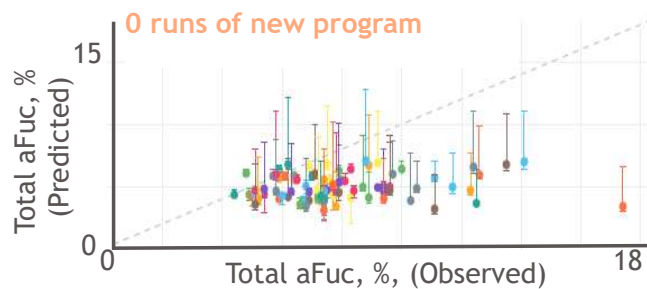
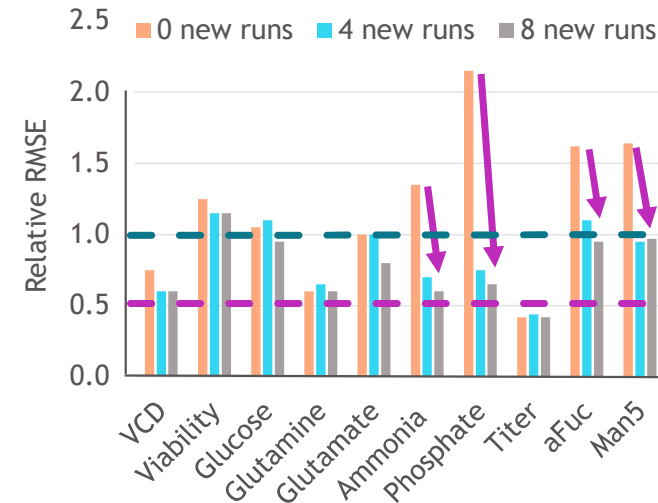


Knowledge transfer is key to enable model-first in process development

Similarity Assessment



Model Error

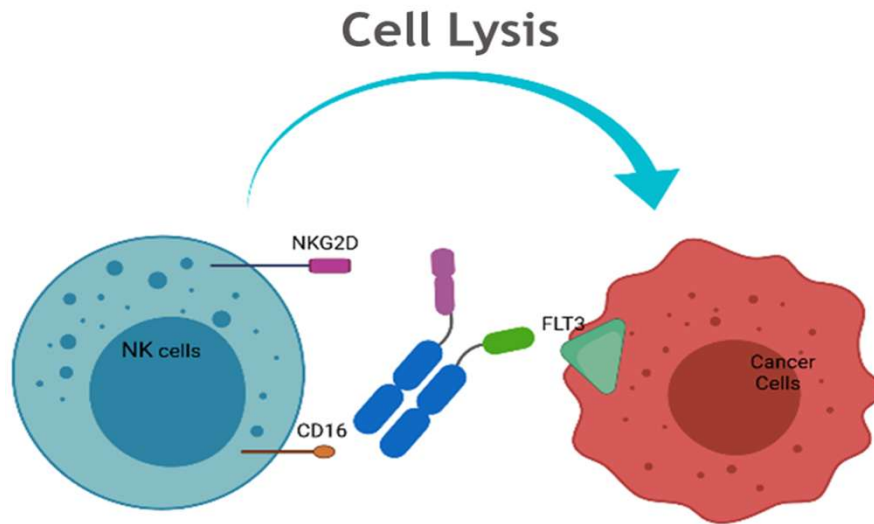


Case Study 2:

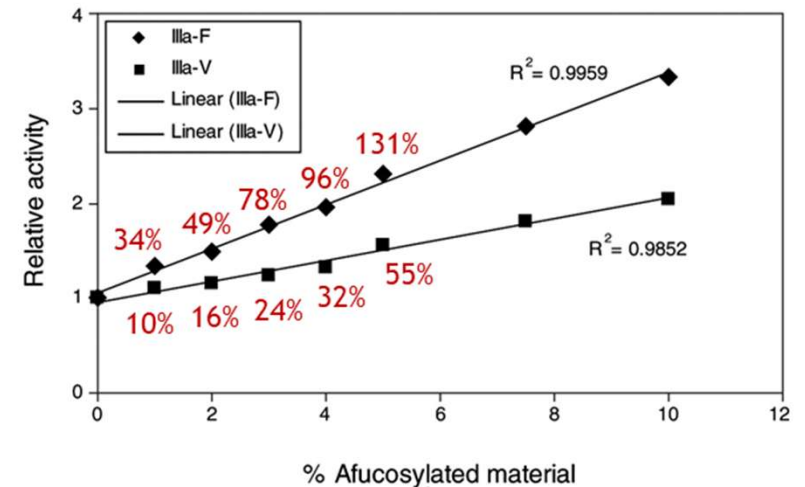
Recipe-Driven Process Optimization of aFucosylation (Knowledge Transfer Across Scales)

Case Study Credit: Khandaker Siddiquee and Yikun Huang

Why is aFucosylation important?

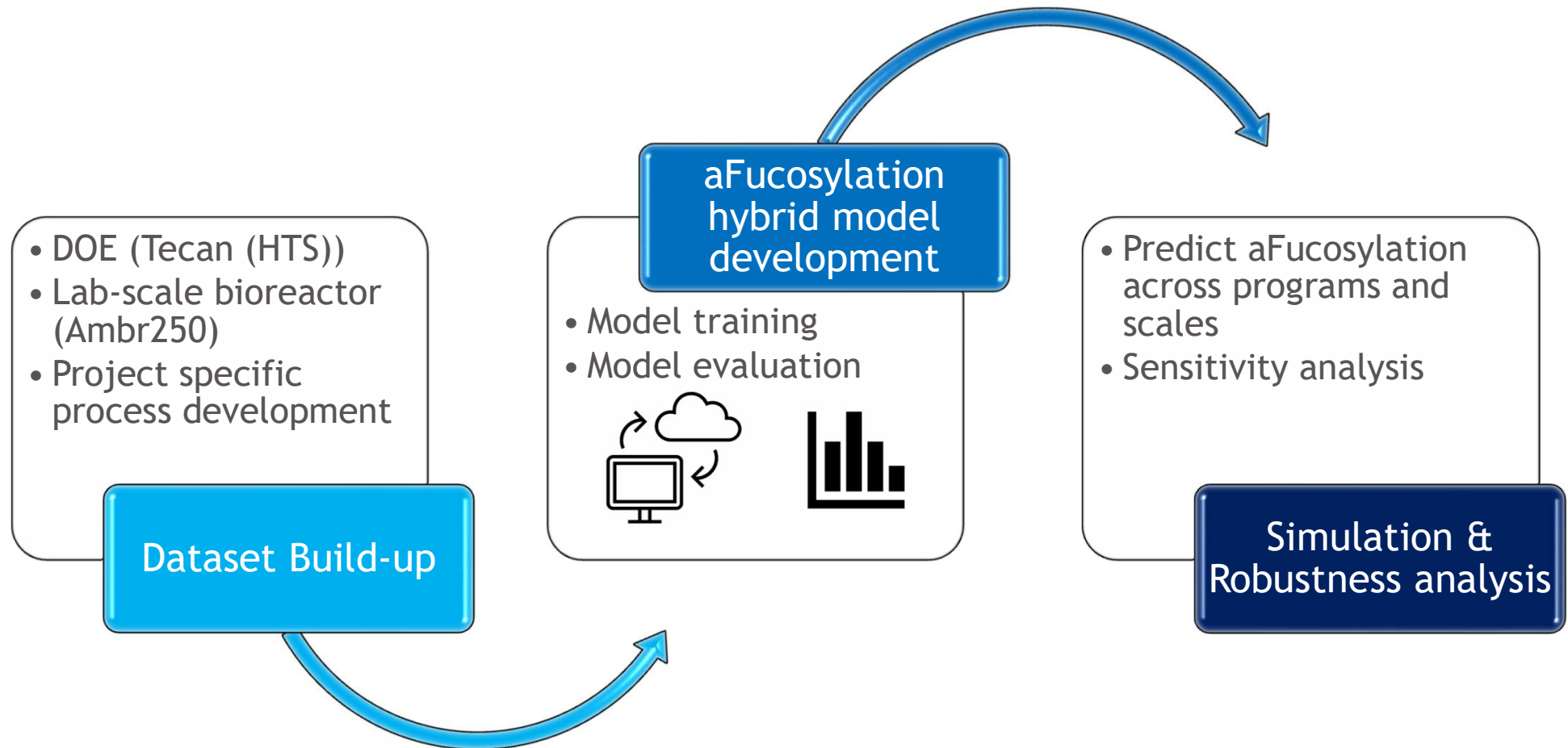


- aFucosylation affects CD16a/FcγRIII binding (efficacy) and antibody dependent cell cytotoxicity (ADCC) (safety)
- Important to **control aFucosylation levels**



Chung, Shan, et al. "Quantitative evaluation of fucose reducing effects in a humanized antibody on Fcγ receptor binding and antibody-dependent cell-mediated cytotoxicity activities." *MABs*. Vol. 4. No. 3. Taylor & Francis, 2012.

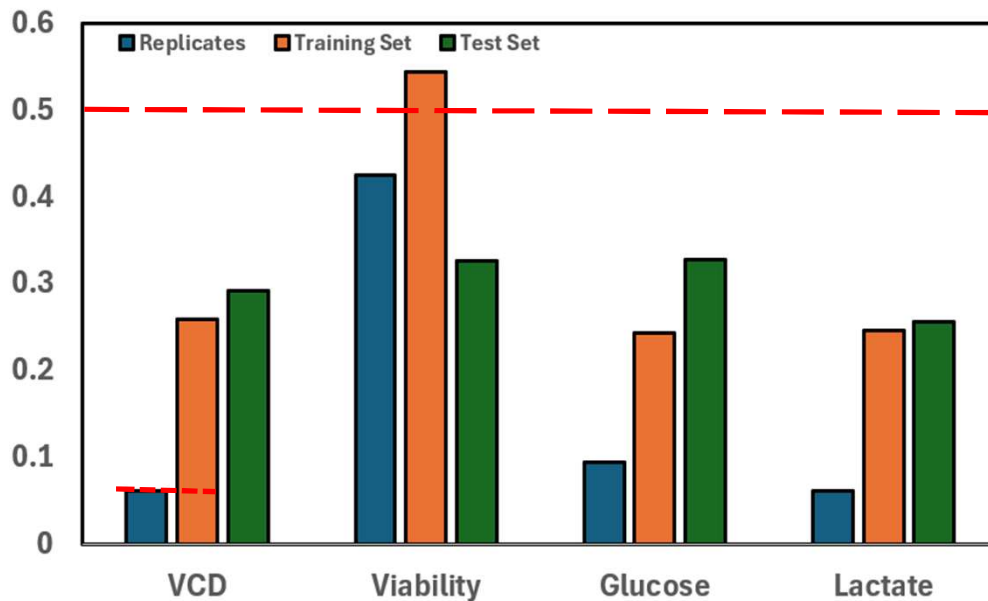
aFucosylation hybrid modeling strategy



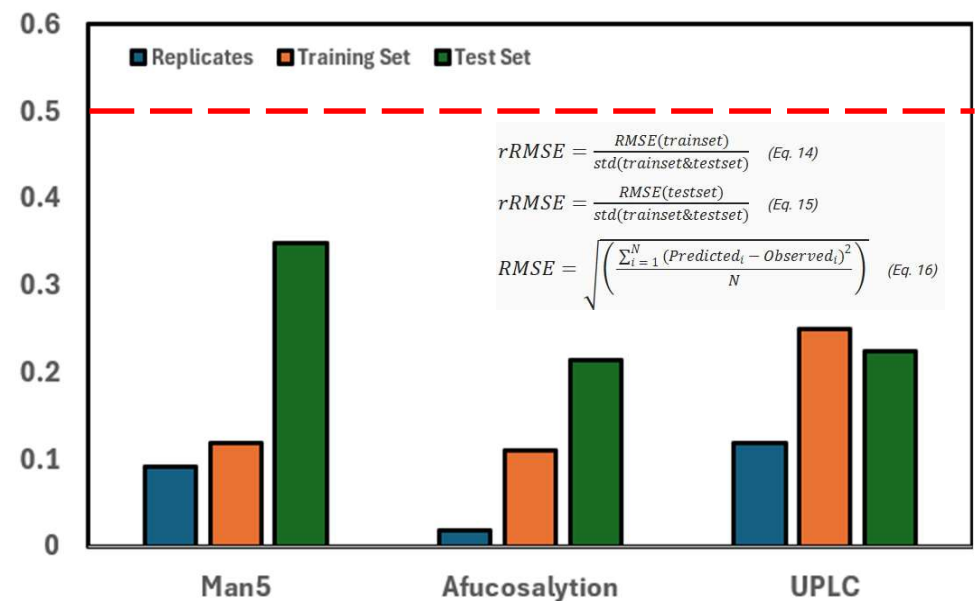
Propagation and historical models show good performance

- Training Set: 63 conditions (54 train, 9 test) from Tecan 50-mL conical high-throughput system (HTS)
- Model outcome:
 - **Good performance** with relative RMSE (rRMSE) < 0.5
 - Except with viability (error prone training data)
 - **No overfitting** (training set rRMSEs are greater than replicate rRMSE)

Propagation Model Relative RMSE

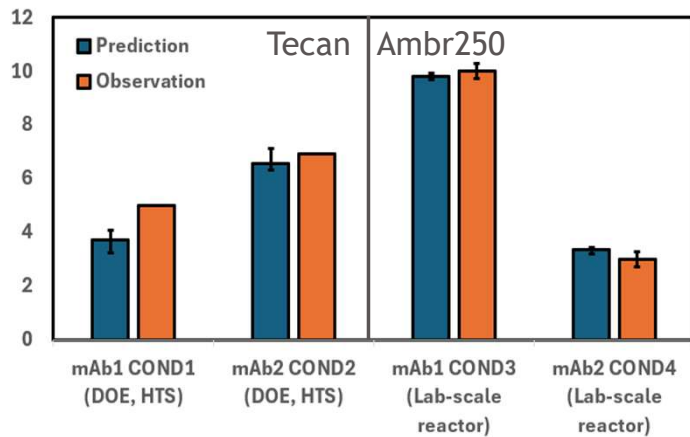


Historical Model Relative RMSE

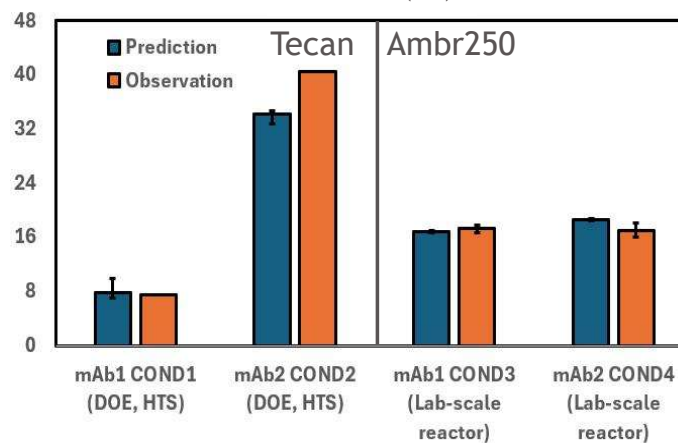


Strong correlation observed between predictions and experimental data for individual conditions for Tecan (HTS) and Ambr250 (Lab) models

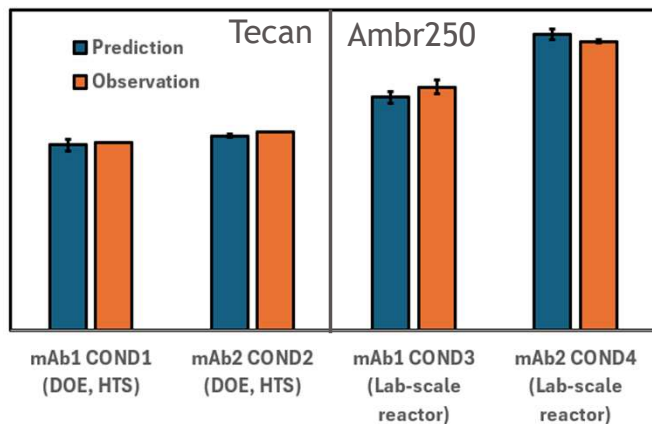
Man5 (%)



aFuc (%)



Titer



2 PROGRAMS, 1 MODEL PER SCALE

Model Training 1

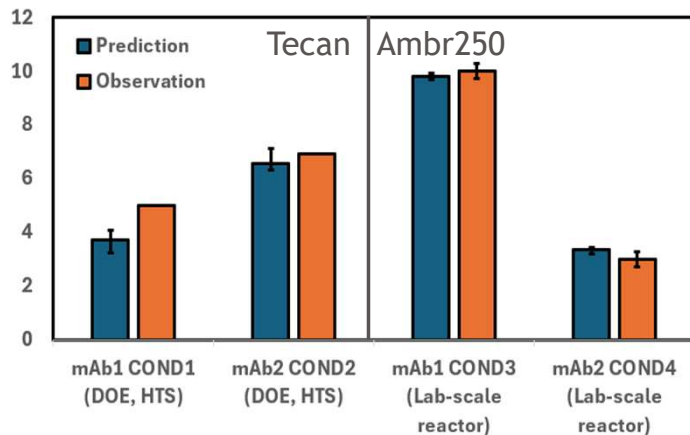
- Tecan: 54 conditions in train set
- AMBR250: 40 conditions in train set

Takeaway 1

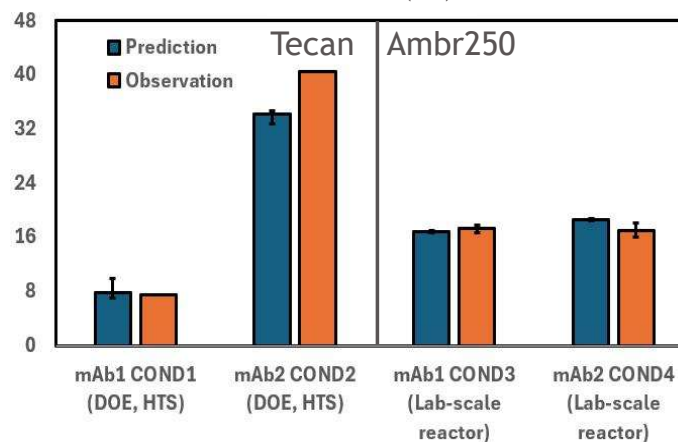
- Accurate prediction of titer and CQAs across programs within scale

Strong correlation observed between predictions and experimental data for individual conditions for Tecan (HTS) and Ambr250 (Lab) models

Man5 (%)



aFuc (%)



2 PROGRAMS, 1 MODEL PER SCALE

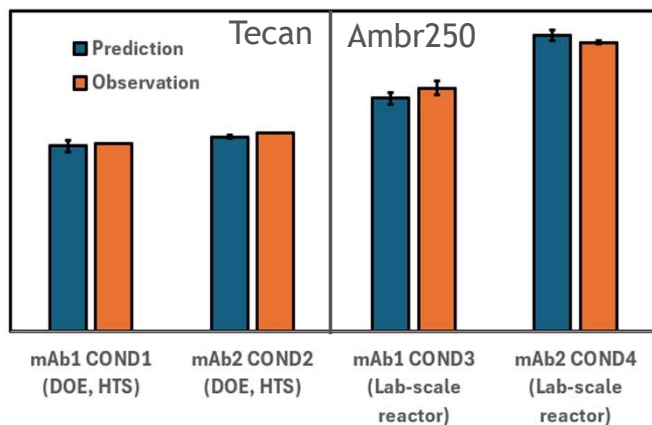
Model Training 1

- Tecan: 54 conditions in train set
- AMBR250: 40 conditions in train set

Takeaway 1

- Accurate prediction of titer and CQAs across programs within scale

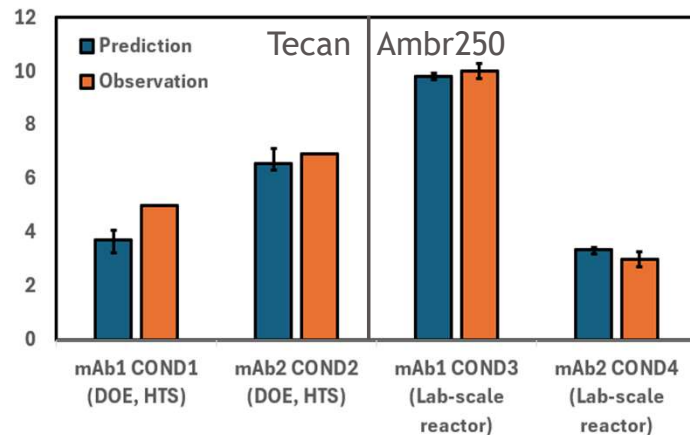
Titer



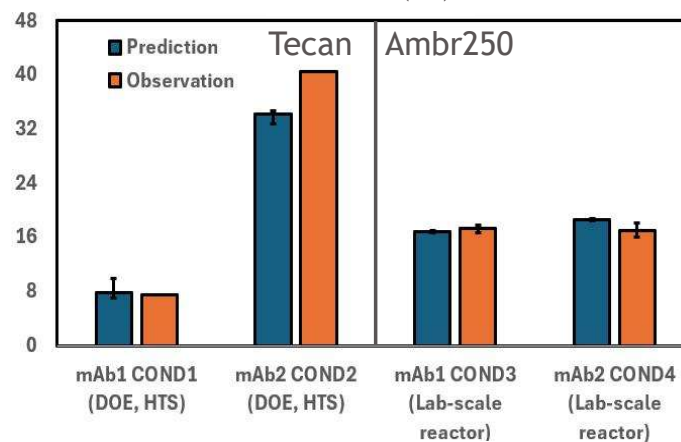
What about across scales?

Strong correlation observed between predictions and experimental data for individual conditions for Tecan (HTS) and Ambr250 (Lab) models

Man5 (%)



aFuc (%)



2 PROGRAMS, 1 MODEL PER SCALE

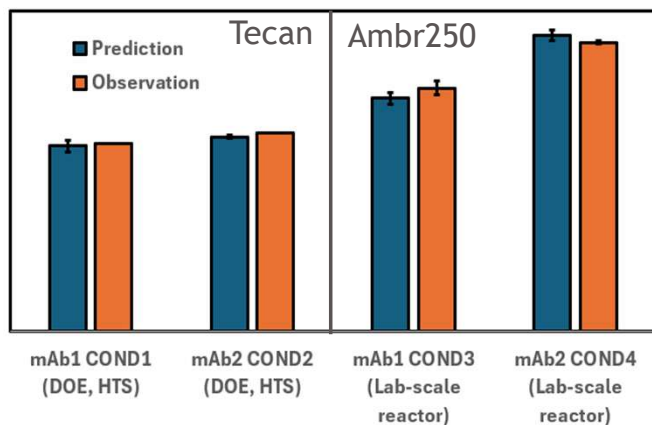
Model Training 1

- Tecan: 54 conditions in train set
- AMBR250: 40 conditions in train set

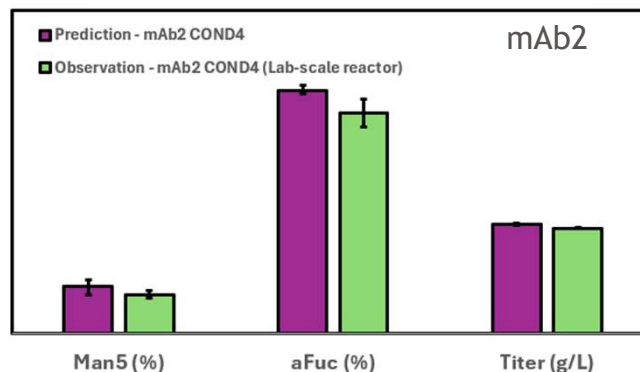
Takeaway 1

- Accurate prediction of titer and CQAs **across programs** within scale

Titer



Prediction Across Scales



2 SCALES, 1 MODEL PER PROGRAM

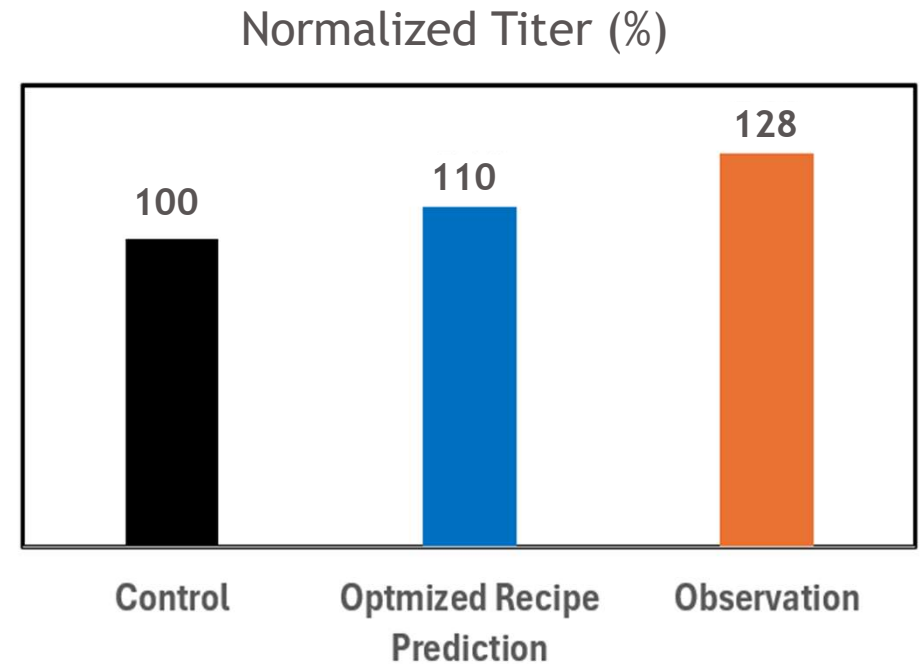
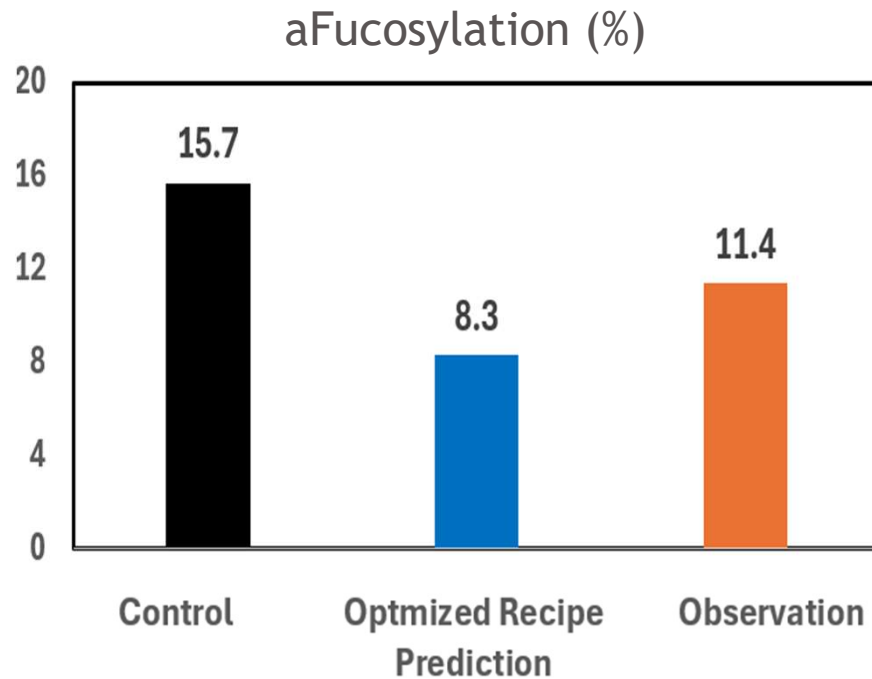
Model Training 2

- 28 conditions from Tecan and 4 conditions from AMBR250 in train set

Takeaway 2

- Accurate prediction of titer and CQAs **across scales**

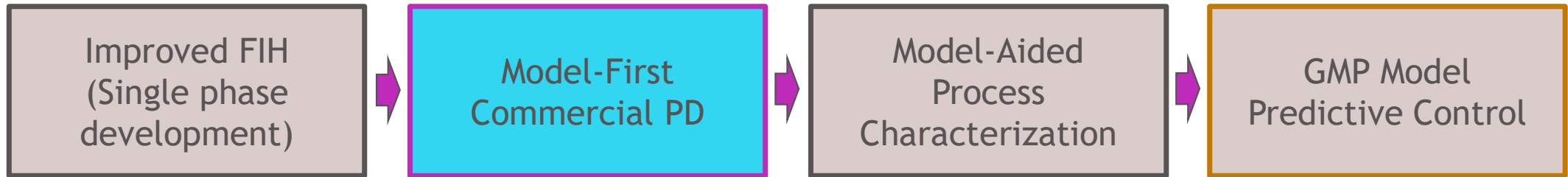
Recipe driven optimization of aFucosylation and titer



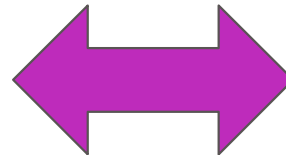
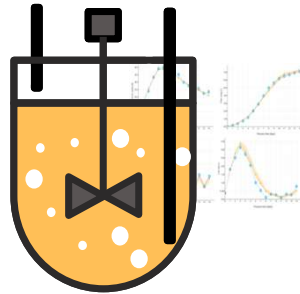
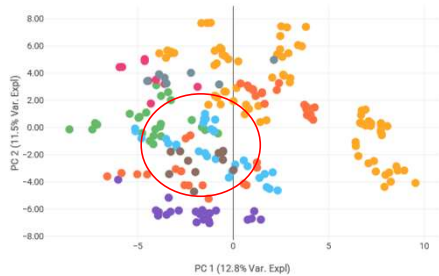
Takeaway

- ✓ Optimization recipes predicted reduced aFucosylation while increasing titer
- ✓ Experimental results align directionally with recipe prediction

North Star Vision for Hybrid Modeling in Cell Culture



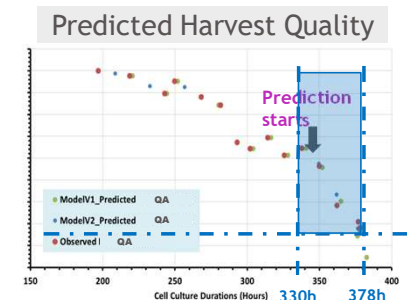
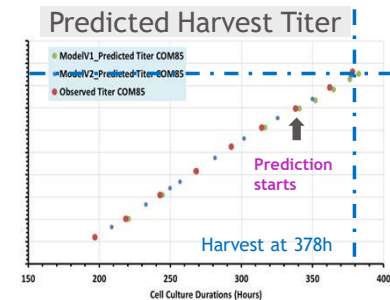
Biologics Development



Goal: Reduce **timelines** of highly **productive** and **robust** process development

Result: 6-week **reduction** in first case

MS&T



Goal: Predict **optimal timing** of process shifts
Maximize **Titer** and **Quality**

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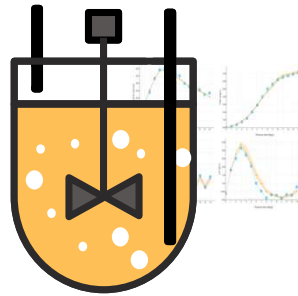
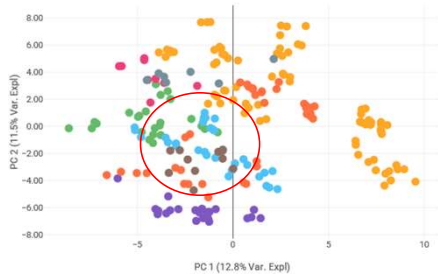
DataHow

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Thank you

Biologics Development



Goal: Reduce **timelines** of highly **productive** and **robust** process development

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