Hybrid modeling framework for bioprocesses with minimal prior knowledge and limited data

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Abstract

A hybrid model combines a mechanistic model, described by ordinary differential equations, with a data-driven component, such as neural networks. This strategy leverages both the physical knowledge of the system and the predictive power of machine learning methods, and it has been applied to a variety of bioprocesses. Nevertheless, it faces important challenges: (I) the often limited availability of experimental data and (II) the incorporation of uncertain mechanistic knowledge. To address these limitations, we propose a framework that generates mathematical models that enforce only minimal yet essential qualitative properties such as: non-negativity of state variables, biogenesis, and the requirement that biomass mediates both substrate uptake and product formation. This avoids reliance on kinetic expressions while ensuring that only certain knowledge is introduced, thus

addressing (I). Because batch cultures are the standard experimental setup in early-stage bioprocess research and are routinely repeated under different conditions, we focus on this type of experiment to address (II). We propose a minibatch optimization scheme based on the ADAM optimizer, where each batch experiment naturally corresponds to a minibatch in the algorithm. Using both synthetic and experimental datasets, we show that only a few batch experiments are sufficient to train accurate and generalizable hybrid models, and that incorporating stochastic regularization provides better interpretability to the model. Overall, this work provides a structured and biologically grounded alternative to existing hybrid modeling approaches, improving how machine-learning tools can be integrated into bioprocess modeling under limited data and limited prior knowledge.

Keywords: Data-driven modeling; Batch culture; Neural network; Parameter estimation; Small datasets.

1 Introduction

The concept of hybrid modeling for bioengineering was first proposed by [20] for fermentation process control and has been further developed since the 2000s [7, 17]. Hybrid models integrate a data-driven model and a parametric model (mechanistic/empirical component) into a unified system that benefits from both physical properties and data-driven aspects. The mechanistic part is generally described by a system of ordinary differential equations (ODEs), and the data-driven component is described by a neural network (NN). Hybrid models have been successfully applied in several bioprocesses [1], including the production of biopharmaceuticals with mammalian cells [19, 16], the production of recombinant proteins with *Escherichia coli* [27, 3], and the production of amoxicillin by biocatalysis [24]. Despite their success in several applications, hybrid models face several important challenges.

A first major challenge concerns data availability [11]. Most published studies on hybrid modeling rely on relatively large datasets. For example, [16] reported results based on 81 fed-batch experiments, while [18] used synthetic data derived from 25 fed-batch model simulations. However, during the early stages of process development, it is common to have access to only a few batch experiments. Such limited data can lead to model overfitting. To

avoid this, different stochastic regularization techniques have been employed. In particular, dropout regularization [25], originally developed for deep neural networks, has been recently implemented in hybrid modeling frameworks [18]. Dropout works by randomly deactivating a fraction of neurons during training, preventing the network from relying too heavily on specific connections.

A second challenge concerns the construction of the hybrid model itself. Incorporating uncertain or inaccurate prior mechanistic knowledge can degrade predictive performance and lead to ill-conditioned estimation problems [21]. This issue is particularly pronounced in the early research phases when reliable mechanistic knowledge is often limited. In addition, the introduction of unknown parameters into the mechanistic component further complicates model calibration, requiring the simultaneous estimation of mechanistic parameters and neural network weights, a task known to be computationally demanding and prone to identifiability issues [23]. To mitigate these difficulties, two-step training strategies have often been proposed, in which mechanistic and data-driven components are fitted separately before integration [29].

Motivated by these two challenges, data scarcity and limited mechanistic knowledge, the objective of this paper is to develop and validate a hybrid modeling framework for bioreactors that relies on minimal prior knowledge while enabling efficient training from only a few experiments. Because batch cultures are the standard experimental setup in early-stage bioprocess research and are routinely repeated under different conditions, we focus on this type of experiment to develop hybrid models. By a model with minimal prior knowledge, we refer to a formulation that avoids relying on detailed kinetic expressions or estimated mechanistic parameters. Instead, we aim to develop a modeling framework that incorporates only general, universally accepted physical and biological constraints (e.g., non-negativity, no spontaneous generation of biomass, and biomass-mediated reactions). This keeps the model independent of explicit kinetic assumptions while still ensuring physical plausibility and generalization.

Our framework addresses both the construction of the hybrid model and the use of data during training. On the modeling side, we impose fundamental biological constraints. By relying only on well-established principles, we avoid introducing uncertain assumptions. Using minimal prior knowledge also avoids the need to estimate additional mechanistic parameters. On the training side, we introduce a minibatch training scheme based on the

ADAM optimizer, in which each minibatch corresponds to a single batch experiment. At each iteration, the optimization algorithm refines the model using data from one batch experiment, mimicking the sequential process of calibration across experiments. This approach differs from conventional methods [18], where randomly sampled data points form minibatches. Such conventional strategies are less natural in the context of batch bioreactors, where data are inherently organized by experiments ("minibatch") and may require repeated ODE integrations across multiple initial conditions in each optimization iteration. Finally, we incorporate dropout regularization into the training algorithm to reduce overfitting.

The paper is organized as follows. Section 2 presents the proposed modeling framework. We begin by introducing a general hybrid model that serves as a flexible foundation, and then we describe the procedure to adapt this model for specific bioprocess scenarios. This section also details the algorithm developed to calibrate hybrid models within the proposed framework. Section 3 demonstrates the approach through two case studies: the first employs a synthetic dataset for *E. coli*, while the second applies the method to experimental data on astaxanthin production by *X. dendrorhous*. Finally, the paper concludes with a summary of the main findings and a discussion of perspectives for future research.

2 Hybrid modeling framework

2.1 Hybrid model

Let us consider a closed system in which microorganisms grow. Let

$$\xi = (\xi_1, \ldots, \xi_n) \in \mathbb{R}_+^n, \tag{1}$$

where $\mathbb{R}_+$ denotes the set of non-negative real numbers, and let $\mathcal{I} := \{1, \ldots, n\}$ be the associated index set. Typically, ξ corresponds to a vector containing the concentrations of biomass, substrates, and products. We propose the following set of differential equations to describe the dynamics of ξ:

$$\frac{d\xi_i}{dt} = f_i(\xi;\theta) \cdot \xi_i \cdot \prod_{j \in M_i^{(f)}} \xi_j \; + \; g_i(\xi;\theta) \cdot \prod_{j \in M_i^{(g)}} \xi_j, \qquad i \in \mathcal{I}, \tag{2}$$

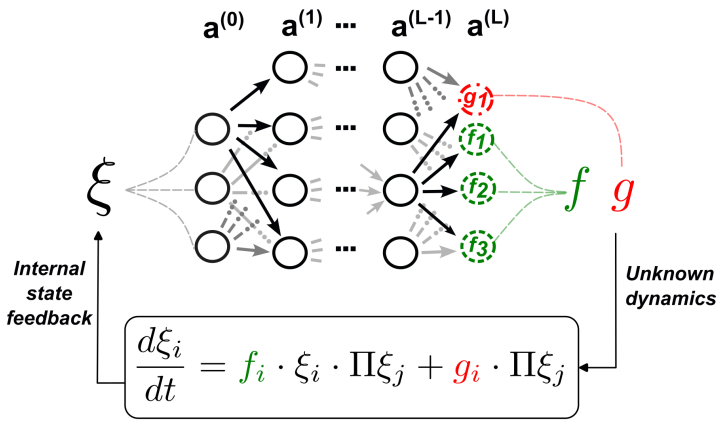

Figure 1: Scheme of the hybrid model. A NN is used to describe the functions f_i and g_i, which receive the state vector as input layer. The NN consist of layers $a^l, l \in \{0, .., L\}$. On the right hand side of the ODE, the functions g_i and f_i are multiplied by state variables. The function f_i is necessarily multiplied by ξ_i, which ensures non-negativity of the solutions (see Proposition 1).

where $f_i : \mathbb{R}^n \times \Theta \to \mathbb{R}$ and $g_i : \mathbb{R}^n \times \Theta \to \mathbb{R}_+$ are described by feedforward neural networks (FNN). An FNN is a standard machine-learning model used to approximate unknown nonlinear relationships directly from data (details are presented in Section 2.3). The set Θ denotes the parameter space of the FNN, that is, the set of all admissible weights and biases. A specific configuration of these parameters is represented by $\theta \in \Theta$, which corresponds to the complete vector of unknown coefficients learned during training. Note that, by definition, the functions $g_i, i = 1, ..n$ are non-negative. The index sets $M_i^{(f)}$ and $M_i^{(g)}$ specify the variables that multiply the functions f_i and g_i, respectively. The particular choice of these sets depends on the system under study and reflects qualitative knowledge, such as biomass-mediated uptake or product formation. By convention, an empty product equals one, *i.e.* $\prod_{j \in \varnothing} \xi_j := 1$; thus, if $M_i^{(f)} = \varnothing$ (resp. $M_i^{(g)} = \varnothing$), the corresponding product does not introduce additional dependencies.

For each state variable ξ_i, the right hand side (RHS) in (2) involves two functions, f_i and g_i. The function g_i represents the generation of the metabolite ξ_i that can occur independently of its current concentration. The function f_i captures the part of the dynamics that vanishes in the absence of ξ_i; this

follows from observing that f_i is multiplied by ξ_i. The products of the variables that multiply each function indicate which state variables are required to mediate changes or the formation of other state variables.

The following proposition states that the solutions to (2) are non-negative, provided non-negative initial conditions.

Proposition 1 (Non-negative state variables) *If $\xi_i(0) \geq 0$ for all $i \in \mathcal{I}$, then $\xi_i(t) \geq 0$ for all $t \geq 0$ and all $i \in \mathcal{I}$.*

Proof. By contradiction, let us assume that there is a time t such that $\xi(t) \notin \mathbb{R}^n_+$. This implies the existence of a time $t' > 0$ such that $\xi(t') \in \partial\mathbb{R}^n_+$ (boundary of the positive cone) and an index $i' \in \mathcal{I}$ such that

$$\xi_{i'}(t') = 0 \quad \text{and} \quad \frac{d\xi_{i'}(t')}{dt} < 0, \tag{3}$$

Otherwise, ξ cannot cross the boundary of $\mathbb{R}^n_+$. Since $\xi(t') \in \partial\mathbb{R}^n_+$, we have that $\xi_i(t') \geq 0$ for all $i \in \mathcal{I}$. This implies that

$$\frac{d\xi_{i'}(t')}{dt} = g_{i'}(\xi_{i'}(t'); \theta) \prod_{j \in M^{(g)}_{i'}} \xi_j(t') \geq 0,$$

which contradicts (3). This completes the proof. □

The following proposition shows the flexibility of the formulation (2) in describing different scenarios in which one state variable mediates the dynamics of other variables.

Proposition 2 *Let $i \in \mathcal{I}$. Then:*

(a) If $g_i \equiv 0$, then in the absence of ξ_i there is no net change in ξ_i.

(b) If $j \in M^{(f)}_i \cap M^{(g)}_i$ (i.e., ξ_j appears as a multiplicative factor on the right-hand side of the equation for ξ_i), then in the absence of ξ_j there is no net change in ξ_i.

(c) If $j \in M^{(g)}_i$ (i.e., ξ_j multiplies g_i on the right-hand side of the equation for ξ_i), then when both ξ_j (e.g., biomass) and ξ_i (e.g., product) are absent, there is no net change in ξ_i.

Proof. The proof follows directly from noting that, in each situation, the derivative of the state variable becomes zero under the given conditions.

Proposition 2 states some properties of (2) that guide the construction of a model tailored to specific conditions. The procedure is structured into three steps, which are applied to each state variable individually.

2.2 Modeling procedure

Procedure 1 (Construction of the Hybrid Model) *The construction of the hybrid model proceeds through three steps, which progressively transform a first formulation into a model suited to the system under study. Let us conser the state vector from (1).*

Step 1: Initialization *Start from the seed model*

$$\frac{d\xi_i}{dt} = f_i(\xi;\theta)\,\xi_i + g_i(\xi;\theta), \qquad i \in \mathcal{I},$$

where f_i and g_i correspond to the data-driven components of the model. This seed model corresponds to (2) when $M_i^{(g)} = M_i^{(f)} = \varnothing$.

Step 2: Enforcing self-invariance at zero *For each state variable ξ_i, assess whether it can emerge in the absence of itself. If spontaneous appearance is not possible (e.g., for biomass or substrate in closed systems), the generation term is removed by setting*

$$g_i \equiv 0.$$

Step 3: Introducing mediated interactions *Determine which state variables are required for any variation or formation of ξ_i. Variables that modulate all changes of ξ_i multiply the entire RHS, while those that specifically mediate its generation when $\xi_i = 0$ (for instance, biomass enabling product synthesis) multiply only the corresponding generation term.*

We refer the reader to Section 3 to see examples of how this Procedure leads to the construction of models.

Remark. Unlike classical bioprocess hybrid models, which are typically derived from mass balances and specific kinetic expressions [17, 19, 16, 18], the approach adopted here does not rely on any explicit conservation equations or mechanistic rate laws. Instead, the model is constructed from a set of qualitative constraints that encode essential biological principles, such as zero-invariance, biomass-mediated interactions, and the impossibility of spontaneous formation of certain states. These constraints define the admissible structure of the RHS of the ODEs, while the unknown functional dependencies are learned directly from data through neural networks. This strategy enables the formulation of dynamic models that remain biologically consistent without requiring detailed prior knowledge of stoichiometry, reaction pathways, or kinetic forms.

Remark. Note that physical or operational components, such as gas–liquid mass transfer or feed and dilution rate terms, can be readily incorporated into (2) to describe continuous or fed-batch operation. However, if operational parameters affect the kinetics, then they should be considered in the input layer of the neural network.

2.3 Neural network

The functions $f_i(\xi;\theta)$ and $g_i(\xi;\theta)$ in (2) are parameterized by a FNN with L layers. The input layer, denoted by $\mathbf{a}^{(0)}$, corresponds to the state variables, that is, $\mathbf{a}^{(0)} = \xi$. The subsequent hidden layers are computed iteratively as

$$\mathbf{z}^{(\ell)} = W^{(\ell)}\,\mathbf{a}^{(\ell-1)} + b^{(\ell)}, \quad \mathbf{a}^{(\ell)} = \phi^{(\ell)}\big(\mathbf{z}^{(\ell)}\big), \quad \ell = 1,\dots,L,$$

where $\phi^{(\ell)}$ denotes the activation function at layer ℓ. For the hidden layers ($\ell = 1,\dots,L-1$), the activation function is chosen as $\phi^{(\ell)}(u) = \tanh(u)$. The output layer produces

$$\begin{pmatrix} f(\xi;\theta) \\ g(\xi;\theta) \end{pmatrix} = \mathbf{a}^{(L)},$$

where $f = (f_1,\dots,f_n)^T$ and $g = (g_1,\dots,g_n)^T$. The activation function at the output layer is defined elementwise as $\phi^{(L)}(u) = u$ for components corresponding to f_i, and $\phi^{(L)}(u) = \mathrm{ReLU}(u)$ for components corresponding to g_i. This choice ensures that all g_i functions remain non-negative while allowing f_i to take any real value. Finally, the full set of fitting parameters associated with the FNN is given by $\theta = \big\{W^{(\ell)},\, b^{(\ell)}\big\}_{\ell=1,\dots,L}$.

2.4 Available data

In a typical experimental setup aimed at characterizing microbial kinetics, several independent batch experiments are conducted under varying conditions [28, 4, 13, 8]. Let m denote the total number of batch experiments. We will assume that each experiment provides a time series of measurements for all the state variables. Specifically, for the j-th experiment, the available data are of the form,

$$\{(t_{j,0}, \xi_{j,0}^{obs}), (t_{j,1}, \xi_{j,1}^{obs}), ..., (t_{j,n_j}, \xi_{j,n_j}^{obs})\}$$

where $t_{j,k}$ denotes the k-th observation time, and $\xi_{j,k}^{obs}$ represents the corresponding measured concentrations of the state vector. We assume that all state variables are observed; however, in practice, some variables may be unmeasured or only indirectly inferred. The proposed framework can be readily extended to such cases without loss of generality.

In machine learning, it is standard practice to divide the available data into training and validation sets. Here, this division is performed at the *experiment level*. We introduce two index sets, $J_{\text{train}}, J_{\text{val}} \subseteq \{1, \ldots, m\}$, corresponding to the experiments used for training and validation, respectively. Training experiments are used to fit the neural-network parameters within the hybrid model, while validation experiments are held out to assess generalization and detect overfitting. A third set J_{test} may also be included to evaluate predictive performance on completely unseen conditions.

2.5 Training algorithm and implementation

We define the following loss function for the j-th batch experiment:

$$L_j(\theta, \alpha_j) = \underbrace{\frac{1}{n_j+1} \sum_{i=1}^{n} \sum_{k=0}^{n_j} \left(\frac{\xi_i^{\text{model}}(t_{j,k}; \theta, \alpha_j) - \xi_{i,j,k}^{\text{obs}}}{\bar{\xi}_{i,j}^{\text{obs}}} \right)^2}_{\text{mean normalized squared error}} + \underbrace{\lambda_{IC} \sum_{i=1}^{n} \alpha_{i,j}^2}_{\text{regularization term}} \tag{4}$$

where n_j+1 is the number of observation points in experiment j, $\xi_i^{\text{model}}(t_{j,k}; \theta, \alpha_j)$ is the model-predicted value of state i at time $t_{j,k}$, using parameters θ and α_j,

$\xi^{\text{obs}}_{i,j,k}$ is the corresponding measurement, and $\bar{\xi}^{\text{obs}}_{i,j}$ denotes the mean observed value of variable i in experiment j, used to normalize residuals. The vector of parameters $\alpha_j := (\alpha_{1,j}, \ldots, \alpha_{n,j})$, which must be estimated, collects the parameters that define the initial condition of experiment j. Specifically, the model uses

$$\xi^{\text{model}}_i(t_{j,0}; \theta, \alpha) = \xi^{\text{obs}}_{i,j,0} \exp(\alpha_{i,j}). \tag{5}$$

In this way, $\alpha_{i,j} = 0$ recovers the measured initial value and nonzero values allow proportional adjustments while preserving non-negativity. The regularization term in (4) penalizes large deviations of the learned initial conditions from the measured ones, helping control the trade-off between fitting accuracy and robustness.

The global training loss is obtained by aggregating the contributions of all training experiments. We define it as the average of the individual losses:

$$L_{\text{train}}(\theta, \alpha) = \frac{1}{|J_{\text{train}}|} \sum_{j \in J_{\text{train}}} L_j(\theta, \alpha_j). \tag{6}$$

We use $|J_{\text{train}}|$ to denote the cardinality of the index set J_{train}. For validation experiments, the initial conditions are not estimated but directly taken from the observed data. Accordingly, the validation loss is defined as

$$L_{\text{val}}(\theta) = \frac{1}{|J_{\text{val}}|} \sum_{j \in J_{\text{val}}} L_j(\theta,\ 0)\,, \tag{7}$$

where $|J_{\text{val}}|$ denotes the cardinality of the validation set.

Parameter updates are performed using the ADAM optimization algorithm [12], which combines adaptive learning rates with momentum to achieve efficient and stable convergence. We consider two ways of computing gradients:

- **Global step**: The gradient of the total loss L_{total} is computed at each optimization iteration. This corresponds to what is commonly referred to as full-batch optimization [26]. We use the term *global step* to avoid confusion with the notion of batch experiment.

- **Minibatch step**: Gradients are computed using a single loss term L_j at a time. In the minibatch setting adopted here, we generate a random permutation of the experiment indexes $\{1, \ldots, m\}$ at the beginning of each epoch, and the parameters are updated sequentially

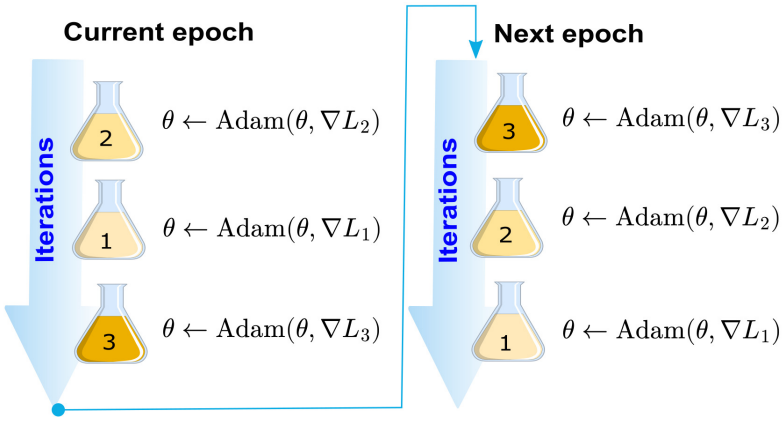

Figure 2: Illustration of the minibatch training strategy considering three batch experiments. In this approach, each batch culture experiment is treated as an individual minibatch, aligning the optimization process with the natural structure of bioprocess data. One epoch corresponds to a full pass through all experiments, with model parameters updated after processing each experiment using the ADAM optimizer. For simplicity, the scheme only illustrates the update of θ.

according to the gradients of the corresponding L_j. Therefore, each epoch processes all batch experiments exactly once, while each update reflects the information contained in one experimental condition (see Figure 2).

Because the available data are limited, we apply dropout regularization during training to prevent overfitting [25]. In this scheme, a fixed fraction of neurons in the hidden layers is randomly deactivated at each iteration, forcing the network to learn more robust and distributed representations while maintaining consistent dynamics across each ODE integration.

The neural network training and hybrid ODE simulations are implemented in Python using the JAX library [5] to leverage automatic differentiation and just-in-time (JIT) compilation for efficient computations on TPU devices. The ADAM optimizer from the Optax library was used to update parameters. All computations, including neural network forward passes and ODE integrations, were JIT-compiled and executed on a TPU v5e-1 device.

To initialize the weights of the neural network, we adopt a two-step initialization process. First, all weights are drawn i.i.d. from a uniform distri-

bution $U(-0.1, 0.1)$. Second, we pretrain the network to satisfy $f_i(\xi, \theta) = 0$ and $g_i(\xi, \theta) = 0$ for all $i \in \mathcal{I}$, yielding an identically zero vector field. Thus, all state variables remain constant at their initial conditions at initialization, providing a neutral and numerically stable starting point for training.

3 Applications

The purpose of this section is to demonstrate the application of the hybrid modeling framework introduced in Section 2 through two illustrative examples. We outline how to construct hybrid models using Procedure 1, and we compare different training strategies, with particular emphasis on the minibatch approach introduced in Section 2.5. We then assess the predictive performance of the resulting models and examine whether the FNN component exhibits interpretable behavior. A comprehensive architecture search is beyond the scope of this study; instead, we adopt an architecture validated through preliminary tests for stability and representativeness.

All scripts and data used in this section are publicly available at: https://github.com/carlosmvond/hybrid-modelling-of-batch-bioreactors.

3.1 Hybrid model for *E. coli.*

Table 1: CPU time and validation loss (defined by L_{val} in (7)) for different training configurations applied in Section 3.1. The updating step refers to the strategy used to update the model parameters (either *batch* or *global*; see Section 2.5). The dropout rate indicates the fraction of neurons randomly deactivated during training. CPU time corresponds to the total wall-clock time required to complete all epochs. The CPU time and the validation loss (L_{val}) where evaluated after 500 epochs.

Updating step	**Dropout rate**	**CPU time (s)**	**Validation loss**
Minibatch	0.01	11.3	0.078
Minibatch	0	9.8	0.121
Global	0.01	76.9	0.091
Global	0	74.4	0.280

We use synthetic data generated with the model proposed by [15], which describes the growth of *E. coli* on glucose. The model accounts for overflow metabolism, meaning that when the glucose uptake rate reaches a threshold, acetate is produced [2]. Thus, the model has three state variables: biomass (X), glucose (G), and acetate (A) concentration. To construct the training and validation datasets, we simulate four batch experiments with different initial glucose concentrations: 10, 20, 35, and 50 g/L. Three of these conditions (10, 20, and 50 g/L) are used for training, while the intermediate condition (35 g/L) is reserved for validation. This choice ensures that the validation scenario lies within the range of the training conditions, thus avoiding extrapolation. To further assess the generalization capability of the hybrid model, we additionally generate six independent batch experiments for testing. These test batches cover a broader set of initial glucose concentrations (5, 15, 25, 30, 40, and 45 g/L), allowing us to evaluate model performance across both interpolative and moderately extrapolative scenarios.

To formulate a hybrid model, we follow Procedure 1. Step 1 provides the following seed model:

$$\begin{aligned} \frac{dX}{dt} &= f_1(\cdot)\, X + g_1(\cdot), \\ \frac{dG}{dt} &= f_2(\cdot)\, G + g_2(\cdot), \\ \frac{dA}{dt} &= f_3(\cdot)\, A + g_3(\cdot). \end{aligned} \tag{8}$$

Step 2 introduces the variables that are self-invariant at zero. Here, the state variables X (biomass) and G (glucose) cannot be produced spontaneously; thus, we set $g_1 \equiv g_2 \equiv 0$.

Step 3 incorporates the mediated interactions among the variables. Since no substrate consumption or acetate formation occurs in the absence of biomass, the variable X acts as a mediator that multiplies the corresponding RHSs.

The resulting hybrid model reads:

$$
\begin{aligned}
\frac{dX}{dt} &= f_1(\cdot)\, X, \\
\frac{dG}{dt} &= f_2(\cdot)\, G\, X, \\
\frac{dA}{dt} &= f_3(\cdot)\, A\, X + g_3(\cdot)\, X.
\end{aligned}
\tag{9}
$$

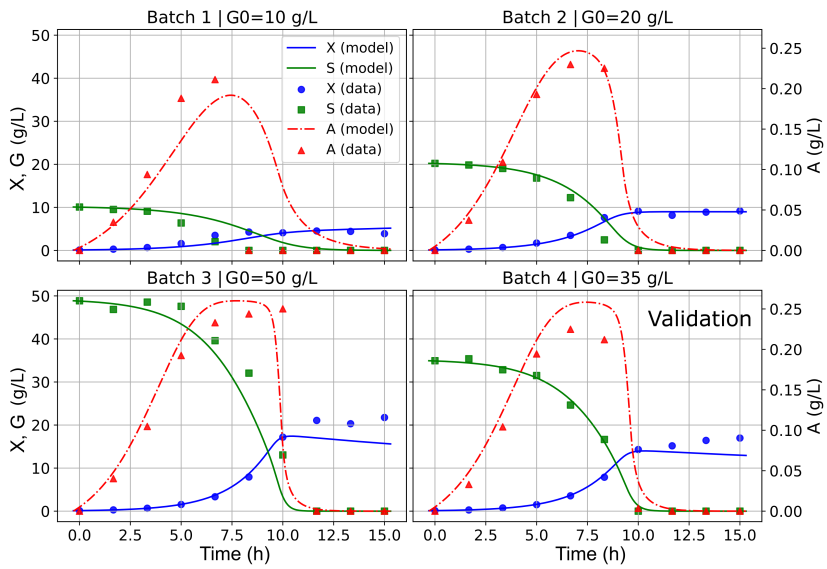

Figure 3: Predicted trajectories generated with model (9) together with the corresponding synthetic data. Solid lines show model predictions, while markers denote the synthetic data points. Biomass (X) and glucose (G) are plotted on the left axis, and acetate (A) on the right axis. Each panel displays the batch number and the initial glucose concentration (G_0). Training was performed using the minibatch strategy with a dropout rate of 0.01, a learning rate of 0.001, and 500 epochs. Determination coefficients are summarized in Table 2.

Note that the variable G could, in principle, also multiply the RHS of the equation for X in (11), assuming that $f_1(\cdot)$ represents the specific growth rate and that growth requires the presence of G. However, $f_1(\cdot)$ may take negative values when G is depleted, reflecting biomass decay [14]. We also note that by selecting suitable forms for the functions f_1, f_2, f_3, and g_3,

model (9) can represent any batch process in which a single metabolite is produced by the microorganism and consumed exclusively through cellular activity.

To assess both the predictive capability of the proposed hybrid model and the effectiveness of the minibatch training strategy, we compare four training configurations using the same FNN architecture, which consists of a single hidden layer with five neurons: (i) minibatch with dropout, (ii) minibatch without dropout, (iii) global training with dropout, and (iv) global training without dropout. All configurations were trained for 500 epochs using the ADAM optimizer with a learning rate of 0.001 and an initial-condition regularization weight $\lambda_{IC} = 1$. As reported in Table 1, the combination of minibatch training and dropout yields the lowest validation loss. Additionally, the minibatch approach reduces the CPU time by approximately a factor of seven compared with the global strategy, both with and without dropout. Figure 3 illustrates the quality of the fit obtained using the minibatch+dropout configuration, showing close agreement between model predictions and experimental data across all states. This is further supported by the R^2 values reported in Table 2, which remain consistently between 0.90 and 0.99 for nearly all training and validation batch experiments.

To assess whether the FFN provides interpretable information, Figure 4 illustrates the learned relationships between the functions f_1 and g_3 appearing in the hybrid model. Although these functions are highly flexible and could in principle take arbitrary shapes, the FNN recovers trends that are biologically meaningful. The function $f_1(\cdot)$ can be interpreted as the specific growth rate, whereas $g_3(\cdot)$ corresponds to the specific acetate production rate. When dropout is included during training, the learned g_3 exhibits a negligible response at low values of f_1 and becomes positive and approximately linear as f_1 increases. This pattern is consistent with the onset of overflow metabolism [2], suggesting that the neural network successfully reconstructs this physiological phenomenon directly from the data. In contrast, the model trained without dropout displays a weaker and less structured relationship, highlighting the role of regularization in revealing interpretable biological dependencies.

Regarding the test data set, we observe that five of the six test batches (Batches 6–10) achieve high predictive accuracy for X and G, with R^2 values between 0.9 and 0.99 for most variables. These conditions lie well within the interpolation region defined by the training experiments. Batches 6, 9, and 10, which are also an interpolation case, show moderate performance with

Table 2: Determination coefficients (R^2) associated with Figure 3, comparing model simulations with experimental data for biomass (X), glucose (G), and acetate (A). Batches 1–3 were used for training, while Batch 4 served for validation. Batches 5-10 are for testing. The column G_0 indicates the experimental initial glucose concentration.

Batch	G_0 **(g/L)**	X	G	A
1	10	0.938	0.964	0.905
2	20	0.977	0.987	0.984
3	50	0.939	0.989	0.956
4	35	0.983	0.967	0.972
5	5	0.274	-0.031	-0.240
6	15	0.940	0.949	0.581
7	25	0.982	0.992	0.957
8	30	0.975	0.977	0.991
9	40	0.974	0.944	0.526
10	45	0.980	0.904	0.454

lower R^2 values for acetate. In contrast, Batch 5 ($G_0 = 5$ g/L) represents true extrapolation beyond the training range and exhibits markedly poorer performance, including negative R^2 values for glucose and acetate. This shows that prediction quality deteriorates when initial conditions fall outside the domain covered during training.

3.2 Hybrid model for astaxanthin production

We use experimental data on astaxanthin production by the yeast *Xanthophyllomyces dendrorhous* reported in [13]. The dataset consists of four batch cultures with measurements of biomass (X), glucose (G), ethanol (E), and astaxanthin (P) concentrations. Each batch differs in its initial glucose concentration: 25, 50, 75, and 100 g/L. The batches with 25, 50, and 100 g/L are used for training, whereas the batch with 75 g/L is reserved for validation.

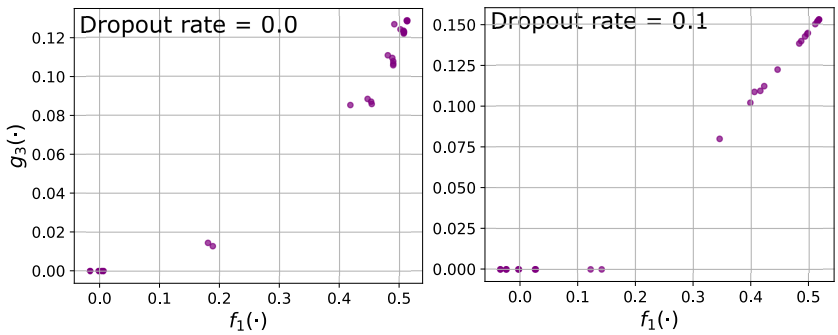

Figure 4: Plot of the relationship between $f_1(\cdot)$ and $g_3(\cdot)$. Both functions are evaluated at the available data for the state variables.

Following Procedure 1, Step 1 provides the generic seed formulation:

$$\begin{aligned}
\frac{dX}{dt} &= f_1(\cdot)\, X + g_1(\cdot), \\
\frac{dG}{dt} &= f_2(\cdot)\, G + g_2(\cdot), \\
\frac{dE}{dt} &= f_3(\cdot)\, E + g_3(\cdot), \\
\frac{dP}{dt} &= f_4(\cdot)\, P + g_4(\cdot).
\end{aligned} \tag{10}$$

Next, Step 2 determines the variables that can increase in their absence. The state variables X (biomass) and G (glucose) cannot be produced in their absence; thus, their generation terms are removed: $g_1 \equiv g_2 \equiv 0$.

Finally, Step 3 incorporates the mediated interactions among the variables. Since substrate consumption cannot occur in the absence of biomass, X acts as a mediator and multiplies the corresponding terms on the RHS. The same rationale applies to ethanol: neither its production nor its consumption can proceed without biomass, and therefore X multiplies its RHS as well. Astaxanthin (P), on the other hand, can only be synthesized in the presence of biomass, yet its concentration does not vanish when $X = 0$ because degradation may still occur. For this reason, X multiplies only the production term $g_4(\cdot)$.

The resulting hybrid model reads:

$$
\begin{aligned}
\frac{dX}{dt} &= f_1(\cdot)\, X, \\
\frac{dG}{dt} &= f_2(\cdot)\, G\, X, \\
\frac{dE}{dt} &= f_3(\cdot)\, E\, X + g_3(\cdot)\, X, \\
\frac{dP}{dt} &= f_4(\cdot)\, P + g_4(\cdot)\, X.
\end{aligned}
\tag{11}
$$

Here, the functions $f_i(\cdot)$ and $g_i(\cdot)$ denote general state- and input-dependent rates defined within our hybrid modeling framework. This formulation naturally encompasses the model proposed by [13].

Remark. The standard model in the literature for describing the production of a metabolite P is the Luedeking–Piret model [10], that is:

$$
\frac{dP}{dt} = a\frac{dX}{dt} + bX, \tag{12}
$$

where a is the growth-associated production coefficient and b is the non-growth-associated production coefficient. However, this model does not ensure the non-negativity of P. Indeed, if $P = 0$, nothing rules out the possibility of dP/dt being negative, thus leading to negative values of the state variable. Moreover, in the absence of biomass, (12) implies that no change in product concentration occur; however product degradation may occur. Thus, (12) may not be appropriate for describing the dynamics of product concentration.

Figure 5 shows the results obtained with the hybrid model trained using an FFN comprising four hidden layers, each with four neurons. As summarized in Table 3, the model achieved consistently high determination coefficients in the training batches, with R^2 values ranging from 0.86 to 0.99 for biomass, glucose, and astaxanthin concentrations, indicating that the learned dynamics capture the experimental trends with good accuracy. The validation batch (Batch 4) also shows satisfactory predictive performance, with R^2 values of 0.76, 0.85, 0.78, and 0.94 for biomass, glucose, ethanol, and the product, respectively. These results suggest that the hybrid model generalizes well to unseen conditions despite being trained with a limited number

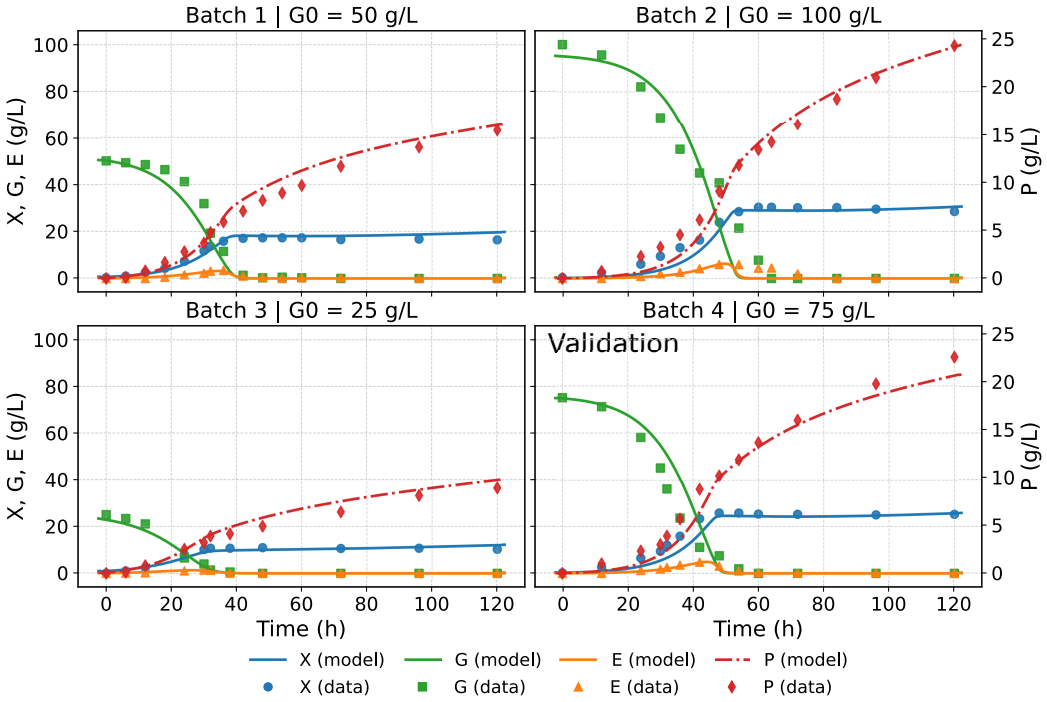

Figure 5: Predicted trajectories generated with model (11) together with the corresponding experimental data. Solid lines show the model predictions for biomass (X), glucose (G), and ethanol (E) on the left axis, and the dash–dot red line shows the product concentration (P) on the right axis. Symbols denote experimental measurements. Each panel reports the initial glucose concentration (G_0). Training employed a minibatch scheme with dropout (0.01), a learning rate of 0.001, and 2000 epochs.

of experiments, demonstrating both robustness and physical consistency in reproducing the coupled growth–production dynamics.

Regarding the interpretability of the FNN, Figure 6 reveals clear functional relationships between the learned terms $g_3(\cdot)$, $g_4(\cdot)$, and $f_1(\cdot)$. The function f_1 can be interpreted as the specific growth rate of the yeast, while g_3 and g_4 represent the specific production rates of ethanol and astaxanthin, respectively. As shown in Figure 6, ethanol production (g_3) becomes significant only once f_1 exceeds a threshold value, a behavior consistent with overflow-like metabolic activation and analogous to the trend observed in the previous application (see Figure 4). In contrast, astaxanthin production (g_4) exhibits an increasing trend with respect to f_1, suggesting a direct association between growth and pigment synthesis under the experimental conditions considered. These results highlight that, despite the model data-driven nature, the FNN component is capable of recovering biologically meaningful dependencies directly from the data.

Table 3: Determination coefficients (R^2), associated with Figure 5, comparing model simulations with experimental data for biomass (X), glucose (G), ethanol (E), and product (P). Batches 1–3 were used for training, while Batch 4 served for validation.

Batch	G_0 **(g/L)**	X	G	E	P
1	50	0.905	0.988	0.955	0.973
2	100	0.859	0.947	0.299	0.961
3	25	0.901	0.972	0.953	0.970
4	75	0.764	0.846	0.775	0.935

4 Conclusions

We have proposed a framework for constructing bioprocess models using minimal prior knowledge of the system and limited data. The effectiveness of this approach was demonstrated in two case studies: one based on synthetic data and the other on real experimental measurements. In both examples, we found that as few as three batch experiments were generally sufficient to train a model that reproduced the main dynamical trends of an unseen batch, although prediction accuracy varied across conditions and variables.

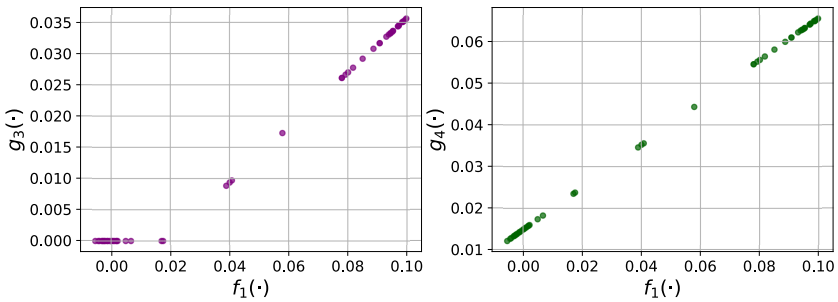

Figure 6: Relationships between the learned specific production rates $g_3(\cdot)$ and $g_4(\cdot)$ and the specific growth rate $f_1(\cdot)$, evaluated at all available experimental data points for the state variables.

Furthermore, the neural network components revealed interpretable structures that align with biologically meaningful behaviors, offering not only predictive capability but also valuable insights into the underlying process dynamics.

We proposed a systematic procedure for formulating the mechanistic component of the hybrid model (see Procedure 1). While most of the hybrid model constructions are based on mass balance principles and/or partially known kinetics, our modeling framework relies on minimal prior knowledge and does not introduce any parameters associated with mechanistic knowledge. This design offers two key advantages for parameter estimation. First, it avoids the need to simultaneously estimate parameters from both the mechanistic model and the machine learning component, a major challenge in hybrid modeling [23], which has often motivated the development of two-step training strategies [29]. Second, we incorporate prior knowledge that is certain and well established. This point is crucial, since including incorrect or uncertain information can degrade model performance and lead to ill-conditioned estimation problems [21]. Together, these features confer a high degree of flexibility to the proposed framework, making it well suited for a broad range of bioprocess scenarios, including those requiring adaptive or incrementally updated models [6].

We introduced a minibatch training strategy inspired by machine-learning practice but tailored to the structure of batch bioprocess data. Unlike the conventional minibatch approach, in which randomly selected data points are used to compute stochastic gradient updates, our method assigns each minibatch to a complete batch experiment. This design exploits the natural

organization of bioprocess data and avoids repeated ODE integrations with heterogeneous initial conditions within a single update. As shown in Section 3, the minibatch scheme achieved a validation loss comparable to that of the global-step method but substantially reduced CPU time. These results demonstrate that adapting classical optimization algorithms to domain-specific data structures can yield both computational and predictive advantages.

Finally, the proposed framework offers new possibilities for developing interpretable models. Whereas recent efforts rely on symbolic regression [9, 22], our formulation enables interpretable structures to be extracted directly from the trained hybrid model, opening a complementary path for identifying underlying dynamics.

Overall, this work introduces a flexible and interpretable hybrid modeling strategy for bioprocesses. By avoiding strong mechanistic assumptions and exploiting the structure of batch experimental data, the framework provides a practical and efficient alternative to traditional hybrid models, contributing to the development of robust modeling tools for early-stage bioprocess research.

Acknowledgments

This work was supported by the National Research and Development Agency (ANID) through FONDECYT Grant No. 11251726, and by the Pontificia Universidad Católica de Valparaíso through Grant No. 039.770/2025. This work was partially supported by ITMO Cancer of Aviesan as part of the 2021–2030 Cancer Control Strategy (MIC proposal Cellema, grant 22CM045-00), via funds administered by Inserm to Jérémie Roux, who served as the postdoctoral supervisor of Marielle Péré.

Data availability statement

The datasets used for model training in this study were obtained from previously published works. Specifically, the synthetic dataset for *E. coli* growth was generated using the model proposed by Mauri et al. [15], while the experimental data for astaxanthin production by *X. dendrorhous* were taken from Liu and Wu [13].

The scripts used for training the models in Section 3 are available in https://github.com/carlosmvond/hybrid-modelling-of-batch-bioreactors.

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