



Identifiability and Identification of Switched Linear Biological Systems

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Difficulties in Biological System Identification



- (1) Biological systems often involve complex biochemical reactions that result in high-order kinetics with many unknown parameters.

- (2) Experimental observations are often limited. It is common that not all the state variables are continuously measurable, which can incur non-unique solution problems and limit the use of parameter identification algorithms.

- (3) Rich perturbations are very important to parameter identification, but there are usually restrictions on executing complex excitation signals.





Research Objective



To analyze the identifiability and identification of a class of switched linear models whose system matrix depends on the input.

$$\dot{\mathbf{x}} = A(u)\mathbf{x} + Bu, \quad \mathbf{x} \in R^n,$$

$$A(u) \in R^{n \times n}, \quad B \in R^{n \times 1}, \quad u \in R^1$$

$$u = \begin{cases} u_0 & 0 \leq t \leq t_d \\ 0 & t > t_d \end{cases}$$





Determination System Eigenvector Matrix

$$A(u_0) = PD_1Q = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \begin{bmatrix} \lambda_1^1 & 0 & \cdots & 0 \\ 0 & \lambda_1^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_1^n \end{bmatrix} \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1n} \\ q_{21} & q_{22} & \cdots & q_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ q_{n1} & q_{n2} & \cdots & q_{nn} \end{bmatrix}$$

$$A(0) = UD_2V = \begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1n} \\ u_{21} & u_{22} & \cdots & u_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ u_{n1} & u_{n2} & \cdots & u_{nn} \end{bmatrix} \begin{bmatrix} \lambda_2^1 & 0 & \cdots & 0 \\ 0 & \lambda_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_2^n \end{bmatrix} \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ v_{n1} & v_{n2} & \cdots & v_{nn} \end{bmatrix}$$





System Response during Excitation

$$\mathbf{x} = \int_0^t e^{\mathbf{A}\tau} \mathbf{B}u(t - \tau) d\tau = \Phi \begin{bmatrix} \frac{1}{\lambda_1^1} e^{\lambda_1^1 \tau} \\ \lambda_1^1 \\ \frac{1}{\lambda_1^2} e^{\lambda_1^2 \tau} \\ \lambda_1^2 \\ \vdots \\ \frac{1}{\lambda_1^n} e^{\lambda_1^n \tau} \\ \lambda_1^n \end{bmatrix}_0^t$$

$$\Phi = \begin{bmatrix} p_{11} \sum_{i=1}^n q_{1i} (\mathbf{B}u_0)_i & p_{12} \sum_{i=1}^n q_{2i} (\mathbf{B}u_0)_i \cdots p_{1n} \sum_{i=1}^n q_{ni} (\mathbf{B}u_0)_i \\ p_{21} \sum_{i=1}^n q_{1i} (\mathbf{B}u_0)_i & p_{22} \sum_{i=1}^n q_{2i} (\mathbf{B}u_0)_i \cdots p_{2n} \sum_{i=1}^n q_{ni} (\mathbf{B}u_0)_i \\ \vdots & \vdots \quad \ddots \quad \vdots \\ p_{n1} \sum_{i=1}^n q_{1i} (\mathbf{B}u_0)_i & p_{n2} \sum_{i=1}^n q_{2i} (\mathbf{B}u_0)_i \cdots p_{nn} \sum_{i=1}^n q_{ni} (\mathbf{B}u_0)_i \end{bmatrix}$$





System Response following Pulse Excitation

$$x_i = [\varphi_i \mathbf{x}(t_d)]^T \begin{bmatrix} e^{\lambda_1^1 t} \\ e^{\lambda_2^2 t} \\ \vdots \\ e^{\lambda_n^n t} \end{bmatrix} = \Psi_i \begin{bmatrix} \frac{1}{\lambda_1^1} e^{\lambda_1^1 t_d} - \frac{1}{\lambda_1^1} \\ \frac{1}{\lambda_1^2} e^{\lambda_1^2 t_d} - \frac{1}{\lambda_1^2} \\ \vdots \\ \frac{1}{\lambda_1^n} e^{\lambda_1^n t_d} - \frac{1}{\lambda_1^n} \end{bmatrix}^T \begin{bmatrix} e^{\lambda_2^1 t} \\ e^{\lambda_2^2 t} \\ \vdots \\ e^{\lambda_2^n t} \end{bmatrix} \quad \varphi_i = \begin{pmatrix} u_{i1} v_{11} & u_{i1} v_{12} & \cdots & u_{i1} v_{1n} \\ u_{i2} v_{21} & u_{i2} v_{22} & \cdots & u_{i2} v_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ u_{in} v_{n1} & u_{in} v_{n2} & \cdots & u_{in} v_{nn} \end{pmatrix}$$

$$\Psi_i = \begin{pmatrix} u_{i1} \sum_{r=1}^n q_{1r} (Bu_0)_r \sum_{j=1}^n p_{1j} v_{j1} & u_{i1} \sum_{r=1}^n q_{2r} (Bu_0)_r \sum_{j=1}^n p_{1j} v_{j2} & \cdots & u_{i1} \sum_{r=1}^n q_{nr} (Bu_0)_r \sum_{j=1}^n p_{1j} v_{jn} \\ u_{i2} \sum_{r=1}^n q_{1r} (Bu_0)_r \sum_{j=1}^n p_{2j} v_{j1} & u_{i2} \sum_{r=1}^n q_{2r} (Bu_0)_r \sum_{j=1}^n p_{2j} v_{j2} & \cdots & u_{i2} \sum_{r=1}^n q_{nr} (Bu_0)_r \sum_{j=1}^n p_{2j} v_{jn} \\ \vdots & \vdots & \ddots & \vdots \\ u_{in} \sum_{r=1}^n q_{1r} (Bu_0)_r \sum_{j=1}^n p_{nj} v_{j1} & u_{in} \sum_{r=1}^n q_{2r} (Bu_0)_r \sum_{j=1}^n p_{nj} v_{j2} & \cdots & u_{in} \sum_{r=1}^n q_{nr} (Bu_0)_r \sum_{j=1}^n p_{nj} v_{jn} \end{pmatrix}$$





Identifiability Analysis

(I) All States Measurable

- Φ can be determined from experimental data from a single pulse excitation. Since each column vector of Φ is just a multiple of the column vector of the P matrix, Φ itself is another eigenvector matrix for $A(u_0)$. $A(u_0)$ can thus be uniquely reconstructed.
- $A(0)$ can be determined from a single pulse excitation if at least n data points of all the states are measured after the pulse is turned off.





(II) Partial States Measurable and Recurrent-pulse Excitation

- A common and most limiting case is that only one state variable is measurable.
- By using the Vandermonde determinant, it is easy to verify that $\mathbf{x}(t_1), \mathbf{x}(t_2) \dots \mathbf{x}(t_n)$ are linearly independent, where $\mathbf{x}(t_1), \mathbf{x}(t_2) \dots \mathbf{x}(t_n)$ are the state variable values at the end of pulses with durations $t_1, t_2 \dots t_n$, respectively. The measured state variable responses will allow unique determination of the Ψ_i matrix, which provides constraints for the eigenvectors for both $A(u_0)$ and $A(0)$.
- We refer to the repeated application of pulses as recurrent-pulse excitation.





(a) Known $A(u_0)$ --the whole system is identifiable even if only one state variable is measurable.

(1) For the j^{th} recurrent pulse excitation, let ξ_j denote $\varphi_i \mathbf{x}(t_j)$ and ξ_j .

ξ_j can be calculated from the i^{th} measurable state.

(2) Let $X_0 = [\mathbf{x}(t_1), \mathbf{x}(t_2), \dots, \mathbf{x}(t_n)]$ and $\xi = [\xi_1, \xi_2, \dots, \xi_n]$, then

$$\varphi_i = \xi X_0^{-1}$$

(3) Since φ_i is a right eigenvector matrix for $A(0)$, $A(0)$ can be reconstructed as:

$$A(0) = X_0 \xi^{-1} D_2 \xi X_0^{-1} = X_0 M_2 X_0^{-1}$$

where $M_2 = \xi^{-1} D_2 \xi$ |





(b) Known $A(0)$ --the whole system is identifiable even if only one state variable is measurable.



$$\text{Let } X_0 = [\mathbf{x}(t_1), \mathbf{x}(t_2), \dots, \mathbf{x}(t_n)].$$
$$\Phi = X_0 \xi^{-1}$$

$$\text{where } \xi = \begin{bmatrix} \frac{1}{\lambda_1} (e^{\lambda_1 t_1} - 1) & \frac{1}{\lambda_2} (e^{\lambda_2 t_1} - 1) & \dots & \frac{1}{\lambda_n} (e^{\lambda_n t_1} - 1) \\ \frac{1}{\lambda_1} (e^{\lambda_1 t_2} - 1) & \frac{1}{\lambda_2} (e^{\lambda_2 t_2} - 1) & \dots & \frac{1}{\lambda_n} (e^{\lambda_n t_2} - 1) \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{\lambda_1} (e^{\lambda_1 t_n} - 1) & \frac{1}{\lambda_2} (e^{\lambda_2 t_n} - 1) & \dots & \frac{1}{\lambda_n} (e^{\lambda_n t_n} - 1) \end{bmatrix}^T$$

Φ is a left eigenvector matrix for $A(u_0)$

$$A(u_0) = X_0 \xi^{-1} D_1 \xi X_0^{-1} = X_0 M_1 X_0^{-1}$$

$$\text{where } M_1 = \xi^{-1} D_1 \xi . |$$





(c) When none of the matrices are known, a system may still be identifiable if there are sufficient known relationships among the cells of $A(u_0)$ and $A(0)$.

- When there is a linear relationship between $A(u_0)$ and $A(0)$, system identifiability boils down to the unique solution of equation $X_0(aM_1 - bM_2) = CX_0$.
- When the relationships are too complex, another iterative least-squares algorithm can be developed.





Least-squares Algorithm Design for Recurrent-Pulse Excitation



$$\dot{\vec{x}}^j = A(u^j)\vec{x}^j + Bu^j \quad y^j = C\vec{x}^j$$

$$\begin{bmatrix} \dot{\vec{x}}^1 \\ \dot{\vec{x}}^2 \\ \vdots \\ \dot{\vec{x}}^n \end{bmatrix} = \begin{bmatrix} A(u^1) & O & \cdots & O \\ O & A(u^2) & \cdots & O \\ \vdots & \vdots & \ddots & \vdots \\ O & O & \cdots & A(u^n) \end{bmatrix} \begin{bmatrix} \vec{x}^1 \\ \vec{x}^2 \\ \vdots \\ \vec{x}^n \end{bmatrix} + \begin{bmatrix} Bu^1 \\ Bu^2 \\ \vdots \\ Bu^n \end{bmatrix}$$

$$\begin{bmatrix} y^1 \\ y^2 \\ \vdots \\ y^n \end{bmatrix} = \begin{bmatrix} C & O & \cdots & O \\ O & C & \cdots & O \\ \vdots & \vdots & \ddots & \vdots \\ O & O & \cdots & C \end{bmatrix} \begin{bmatrix} \vec{x}^1 \\ \vec{x}^2 \\ \vdots \\ \vec{x}^n \end{bmatrix} \quad z = [y^1 \quad y^2 \quad \cdots \quad y^n]^T$$
$$E = \sum_{r=1}^{sn} (\bar{z}^r - z^r)^T (\bar{z}^r - z^r)$$

$$\Delta k = (\lambda I + \sum_{r=1}^{sn} J_r^T J_r)^{-1} \sum_{r=1}^{sn} J_r^T (\bar{z}^r - z^r)$$

$$k = k + \Delta k$$





An Application of Recurrent-pulse Excitation

$$\begin{Bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \\ \dot{x}_5 \end{Bmatrix} = \mathbf{A} \begin{Bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{Bmatrix} + \begin{Bmatrix} k_1 \\ 0 \\ 0 \\ 0 \\ 0 \end{Bmatrix} u$$

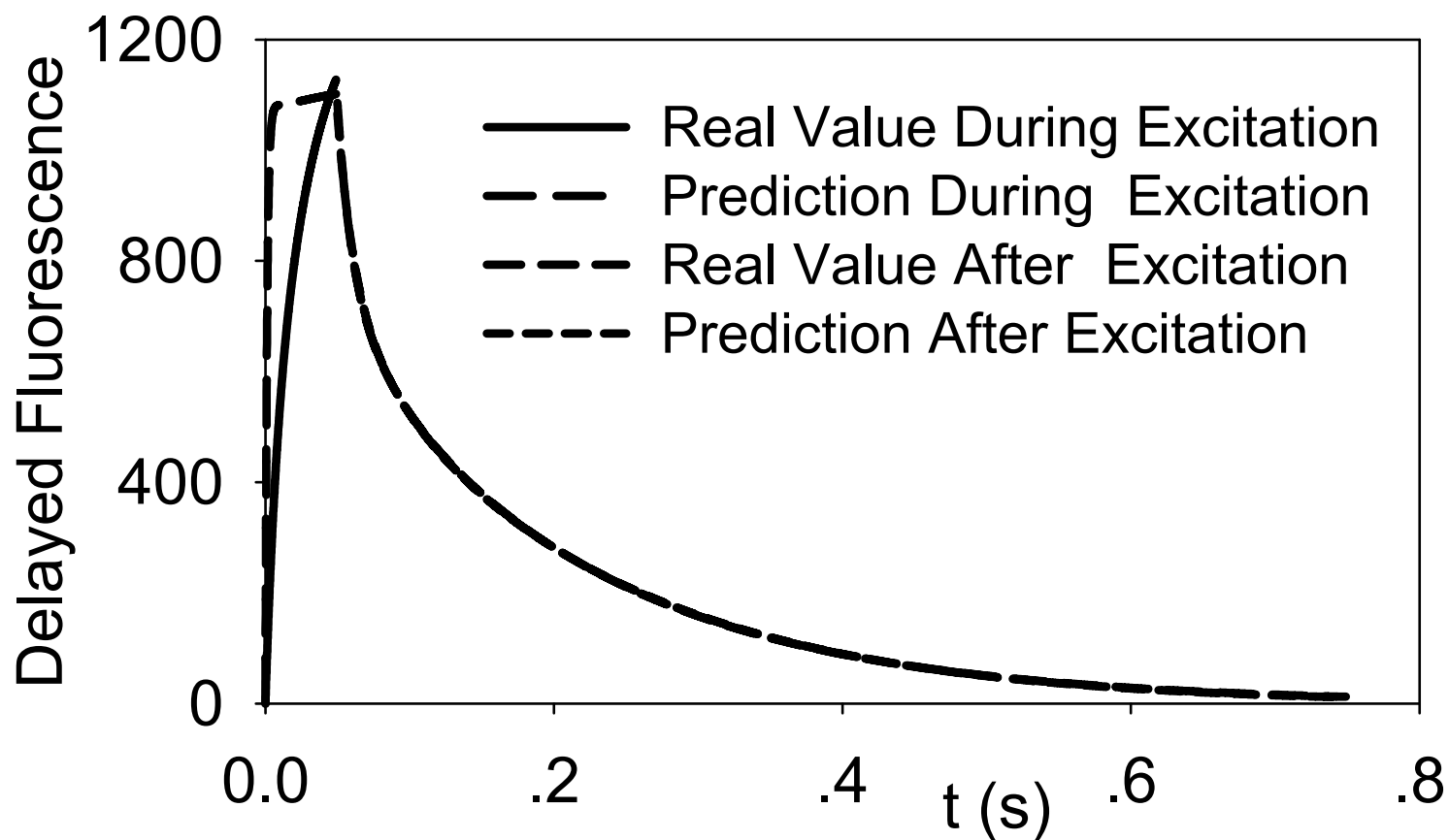
$$y = k_6 k_2 (x_1 + x_3 + x_5)$$

$$\mathbf{A} = \begin{bmatrix} (k_1 u + k_2 + k_3) & (k_1 u - k_4) & k_1 u & k_1 u & (k_1 u - k_5) \\ -k_3 & (k_1 u + k_4) & -k_2 & 0 & 0 \\ 0 & -k_1 u & (k_2 + k_3) & -k_4 & 0 \\ 0 & 0 & -k_3 & (k_1 u + k_4 + k_5) & -k_2 \\ 0 & 0 & 0 & -k_1 u & (k_2 + k_5) \end{bmatrix}$$



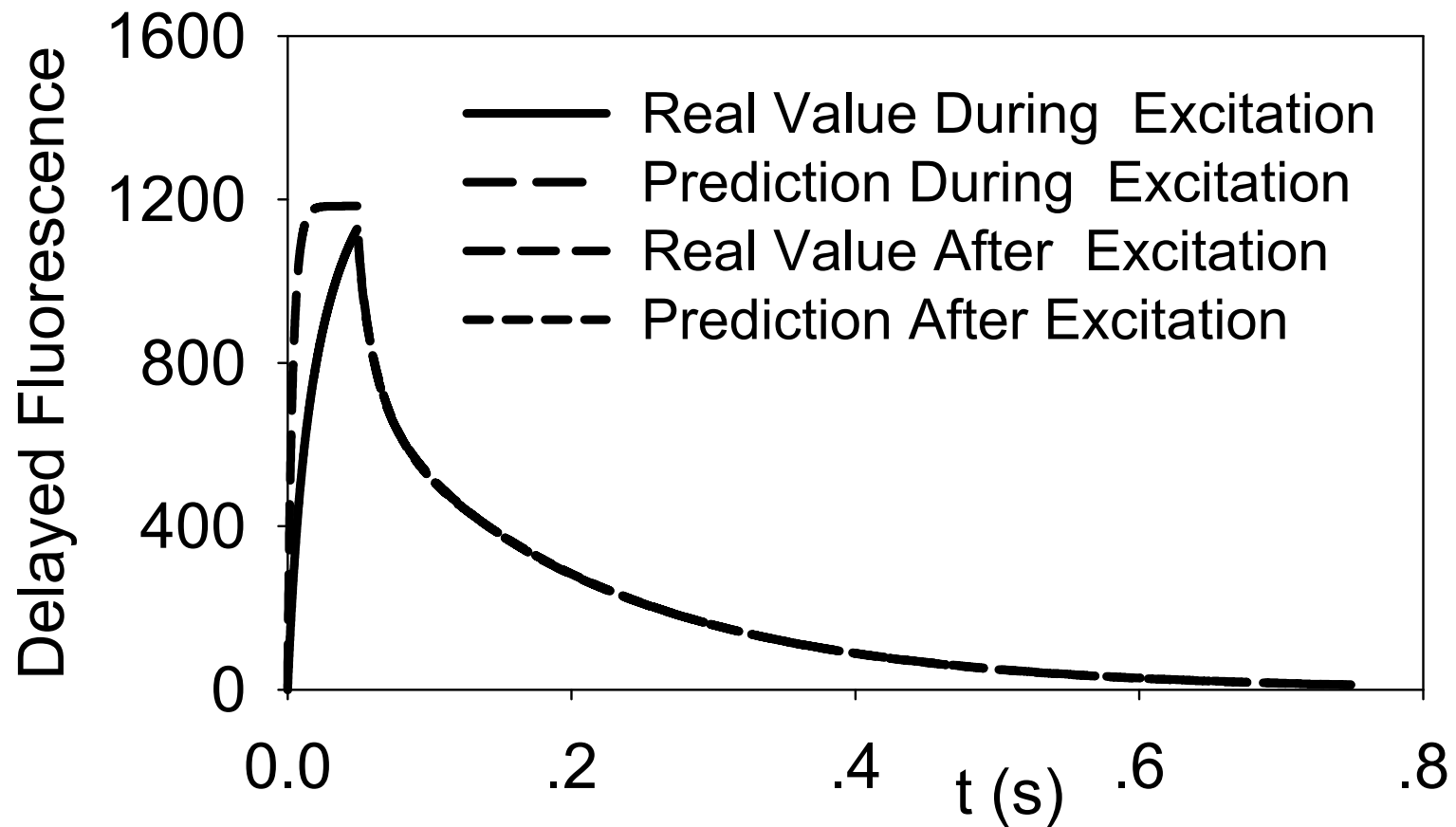


Real Value K_0		26.000	14.000	55.000	44.000	56.000	220.000
Simulation 1	Start at K_{01}	805.284	40.034	85.613	85.346	30.000	483.364
	Converge to K_1	772.723	13.064	37.964	40.535	7.953	88.044



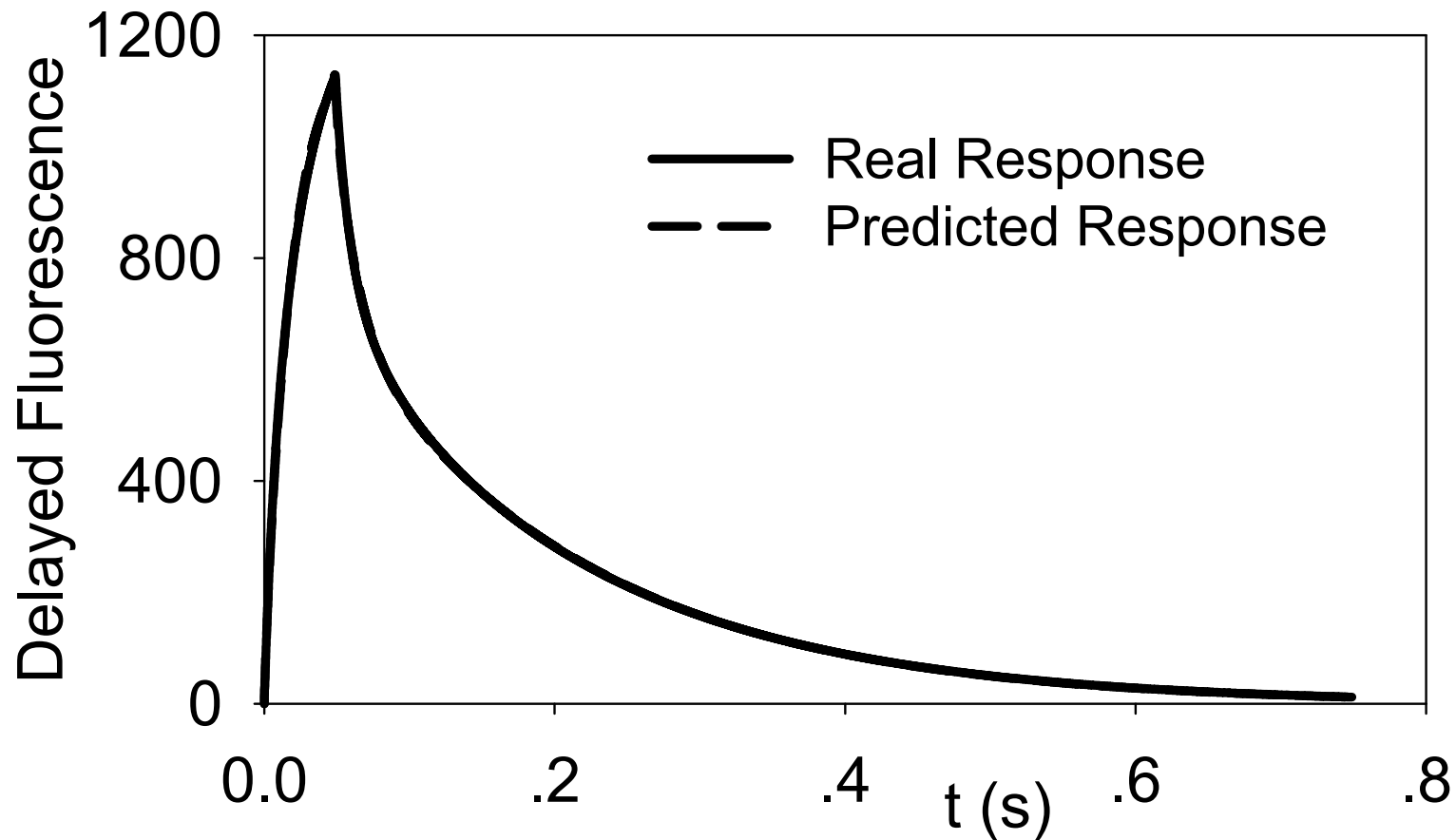


Real Value K_0		26.000	14.000	55.000	44.000	56.000	220.000
Simulation n2	Start at K_{02}	405.284	20.034	45.613	85.346	30.000	883.364
	Converge to K_2	240.361	8.688	210.129	433.444	224.866	185.482



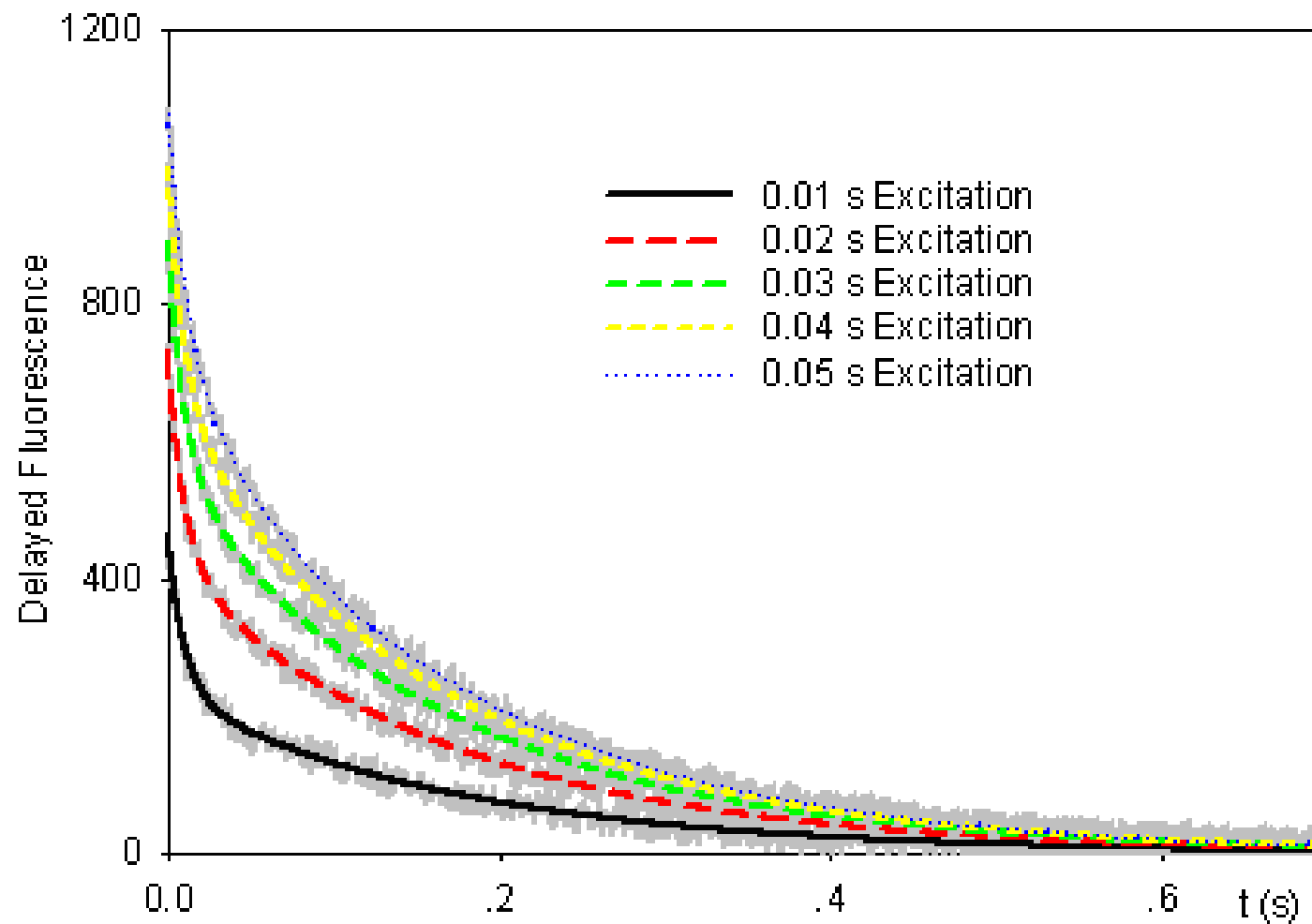


Identification with Light On Data: started at $K_{01}=[805.284, 40.034, 85.613, 85.346, 30.000, 483.364]$ and converged to $K_3=[48.890, 19.132, 1692.604, 740.814, 71.553, 211.858]$





Recurrent Pulse Excitation





Recurrent Pulses Do Not Add New Constraints for a Pure Linear System

Pulses of different durations only provide redundant constraints.

$$\Psi_i = \begin{pmatrix} u_{i1} \sum_{r=1}^n q_{1r} (Bu_0)_r \sum_{j=1}^n p_{1j} v_{j1} & 0 & \cdots & 0 \\ 0 & u_{i2} \sum_{r=1}^n q_{2r} (Bu_0)_r \sum_{j=1}^n p_{2j} v_{j2} \cdots & & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & u_{in} \sum_{r=1}^n q_{nr} (Bu_0)_r \sum_{j=1}^n p_{nj} v_{jn} \end{pmatrix}$$

$$= \begin{bmatrix} p_{i1} \sum_{r=1}^n q_{1r} (Bu_0)_r & 0 & \cdots & 0 \\ 0 & p_{i1} \sum_{r=1}^n q_{2r} (Bu_0)_r & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & p_{i1} \sum_{r=1}^n q_{nr} (Bu_0)_r \end{bmatrix}$$





Summary



Different scenarios of switched linear biological system identifiability were investigated and identification algorithms were developed.

It was found that recurrent-pulse excitation can:

- Avoid long-term effect of excitation and make experiments possible.
- Improve parameter identifiability by providing more constraints.
- Provide data for unmeasurable forced responses.

