



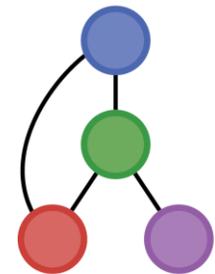
# Robust Dynamic Optimization via Relaxations of Implicit Integration Schemes

**Matthew Wilhelm, PhD Candidate**

Matthew Stuber, Assistant Professor



Conference on  
Computational Science  
and Engineering



Process Systems and  
Operations Research  
Laboratory

# Robust Dynamic Optimization



## Dynamic SIP Formulation

$$\begin{aligned} \Phi^* &= \min_{\mathbf{u}} \Phi(\mathbf{u}) && \longleftarrow \text{Objective} \\ \text{s.t. } g(\mathbf{x}(\mathbf{u}, \mathbf{p}, t_f), \mathbf{u}, \mathbf{p}) &\leq 0 && \longleftarrow \text{Performance Constraint(s)} \\ \dot{\mathbf{x}} &= \mathbf{f}(\mathbf{x}(\mathbf{u}, \mathbf{p}, t), \mathbf{u}, \mathbf{p}) && \longleftarrow \text{Parametric ODEs} \\ \mathbf{x}(\mathbf{u}, \mathbf{p}, t_0) &= \mathbf{x}_0(\mathbf{u}, \mathbf{p}) && \longleftarrow \text{Initial Condition} \\ t &\in I = [t_0, t_f], \forall \mathbf{p} \in P \end{aligned}$$

## Assumptions

- The initial condition  $\mathbf{x}_0: P \rightarrow D$  is locally Lipschitz continuous on  $U \times P$ .
- The right hand side  $\mathbf{f}$  is  $n$  times continuously differentiable on  $U \times D \times P$ .

## Motivation:

- Determine adequate system performance under worst-case realization of uncertainty.
- Key for safety-critical systems and high-risk defect elimination.
- Prior work rely on heuristic approaches which lose strong guarantees [1,2].

1. Puschke, Jennifer, et al. **Robust dynamic optimization of batch processes under parametric uncertainty: Utilizing approaches from semi-infinite programs.** *Computers & Chemical Engineering* 116 (2018): 253-267.
2. Puschke, Jennifer, and Alexander Mitsos. **Robust feasible control based on multi-stage eNMPC considering worst-case scenarios.** *Journal of Process Control* 69 (2018): 8-15.



# Robust Dynamic Optimization



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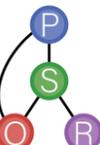
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- Determine adequate system performance under worst-case realization of uncertainty.
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- Prior work rely on heuristic approaches which lose strong guarantees [1,2].

## Relatively general form (via reformulations):

- Applicable to some semi-explicit index-1 DAEs
- Non-autonomous systems

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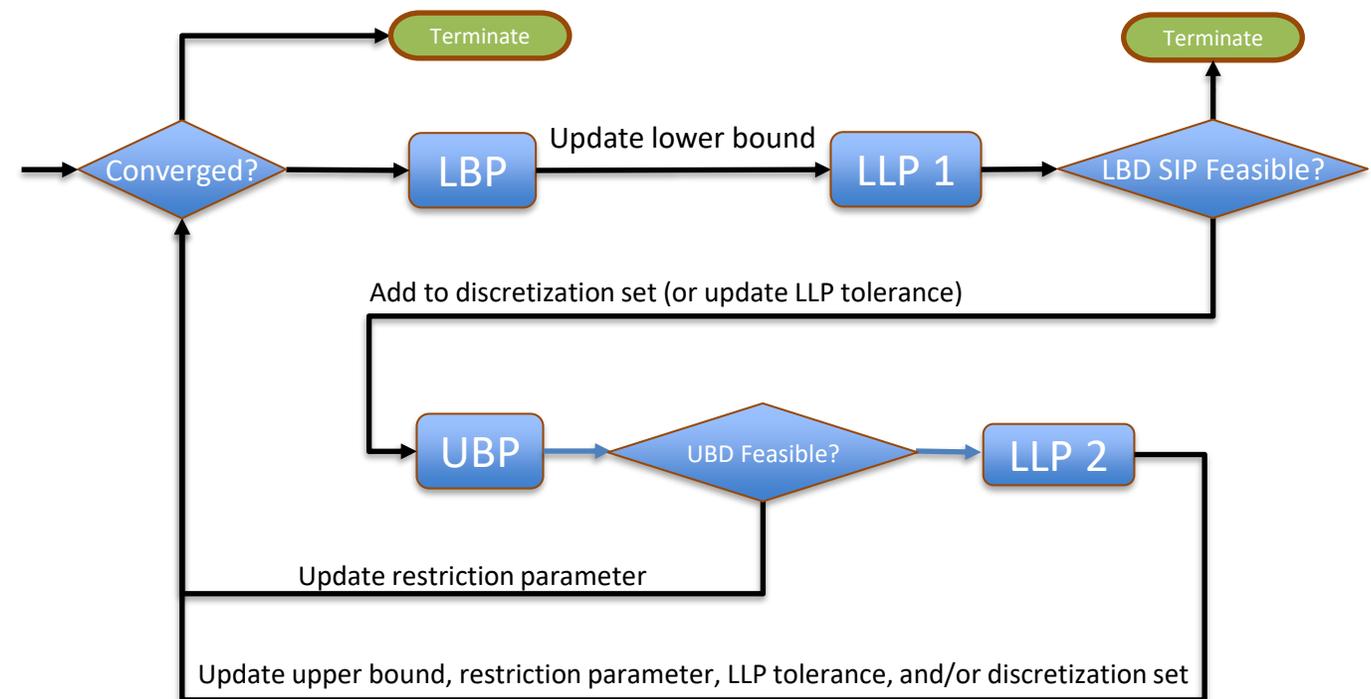


# Semi-infinite Programming



- One standard approach to solving SIP's lies in the discretization the uncertain set [3].
- Restriction-based upper bound incorporated in the SIPres algorithm for nonconvex SIP[4].
- SIPres provides a guaranteed convergence to a global optimal value under Slater-point constraint qualification.
- Adapted to use a hybrid approach which contains an oracle problem that further refines lower and upper bounds at each iteration with a single discretization set per SIP constraint (NOT PICTURED) [5].

## Overview of SIPres algorithm [1]



3. B. Bhattacharjee, P. Lemonidis, W.H. Green Jr, and P.I. Barton. **Global solution of semi-infinite programs**. *Math. Program.* 103 (2005), pp. 283–307.

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# Semi-infinite Programming

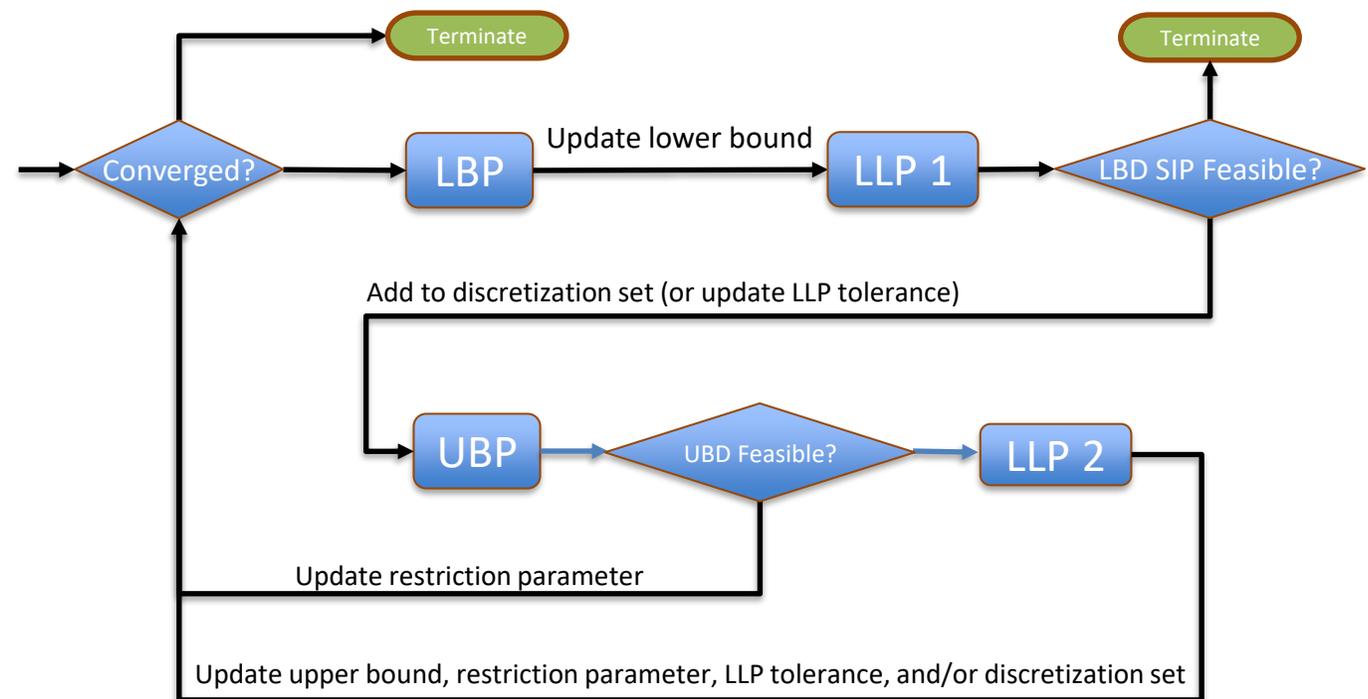


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# SIP Subproblems

LBP

Lower-Bounding Problem

$$\Phi^{LBD} = \min_{\mathbf{u}} \Phi(\mathbf{u})$$

$$s.t. g(\mathbf{x}(\mathbf{u}, \bar{\mathbf{p}}, t_f), \mathbf{u}, \bar{\mathbf{p}}) \leq 0 \quad \forall \bar{\mathbf{p}} \in P^{disc}$$

$$\mathbf{u} \in U \subset \mathbb{R}^{n_u}$$

UBP

Upper-Bounding Problem

$$\Phi^{UBD} = \min_{\mathbf{u}} \Phi(\mathbf{u})$$

$$s.t. g(\mathbf{x}(\mathbf{u}, \bar{\mathbf{p}}, t_f), \mathbf{u}, \bar{\mathbf{p}}) \leq -\epsilon_g \quad \forall \bar{\mathbf{p}} \in P^{disc}$$

$$\mathbf{u} \in U \subset \mathbb{R}^{n_u}$$

LLP

Lower-Level Problem

$$\Phi^{LLP} = \max_{\mathbf{p}} g(\mathbf{x}(\bar{\mathbf{u}}, \mathbf{p}, t_f), \bar{\mathbf{u}}, \mathbf{p})$$

$$s.t. \mathbf{p} \in P \subset \mathbb{R}^{n_p}$$

RES\*

Restriction Problem

$$-\eta^* = \min_{\eta, \mathbf{u}} -\eta$$

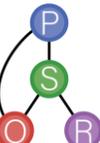
$$s.t. \Phi(\mathbf{u}) - \Phi^{RES} \leq 0$$

$$g(\mathbf{x}(\mathbf{u}, \bar{\mathbf{p}}, t_f), \mathbf{u}, \bar{\mathbf{p}}) \leq -\eta \quad \forall \bar{\mathbf{p}} \in P^{disc}$$

$$\mathbf{u} \in U \subset \mathbb{R}^{n_u}$$

4. Mitsos, Alexander. **Global optimization of semi-infinite programs via restriction of the right-hand side.** *Optimization* 60.10-11 (2011): 1291-1308.

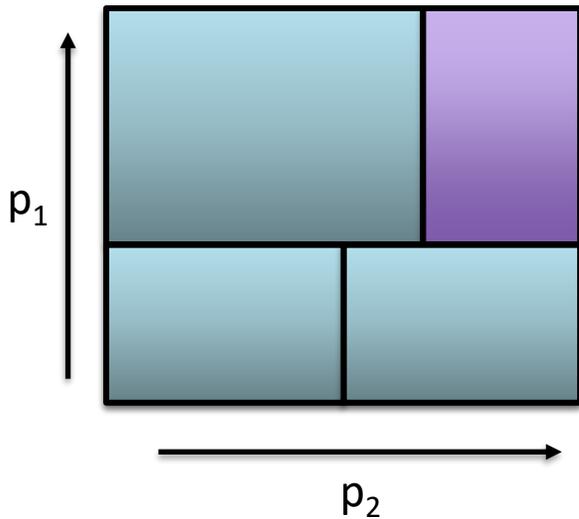
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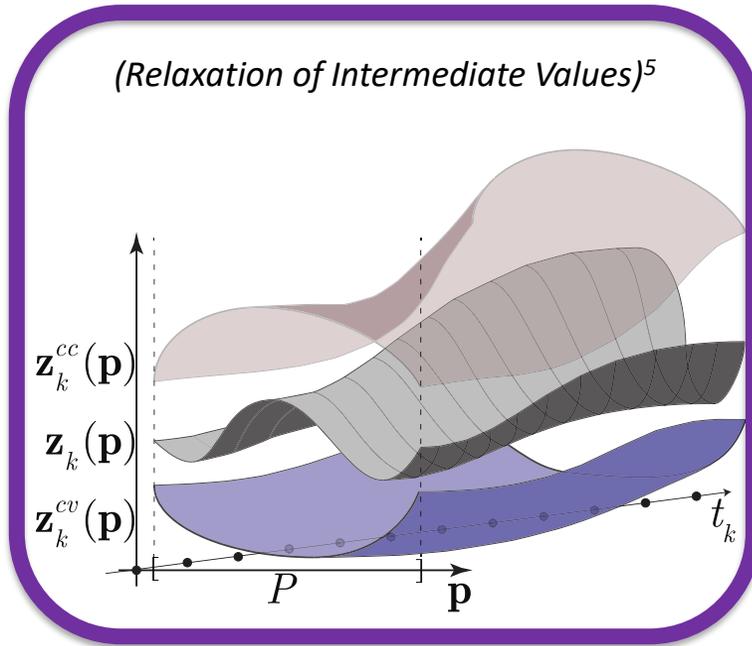
# Global Dynamic Optimization



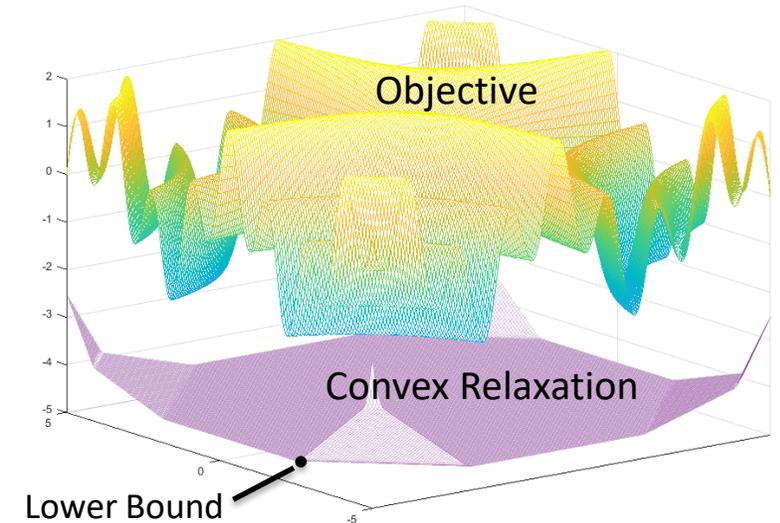
(Selection of Node)



(Relaxation of Intermediate Values)<sup>5</sup>



(Relaxation of Objective and Constraints)



McCormick Operator Arithmetic<sup>7,8,9</sup>

6. Wilhelm, ME; Le, AV; and Stuber, MD. **Global Optimization of Stiff Dynamical Systems**. *AIChE Journal: Futures Issue*, 65 (12), 2019
7. Mitsos, A, et al. **McCormick-based relaxations of algorithms**. *SIAM Journal on Optimization*, SIAM (2009) 20, 73-601.
8. Scott, JK, et al. **Generalized McCormick relaxations**. *Journal of Global Optimization* 51.4 (2011): 569-606.
9. Khan, K. et al. **Differentiable McCormick relaxations**. *Journal Global Optimization* (2017), 67(4), 687-729.



# Reduced-Space Relaxations

## Relax-then-Discretize

$$\begin{aligned} \dot{\mathbf{x}}^{cv}(t, \mathbf{p}) &= \mathbf{f}^{cv}(t, \mathbf{p}, \mathbf{x}^{cv}(t, \mathbf{p}), \mathbf{x}^{cc}(t, \mathbf{p})), & \mathbf{x}^{cv}(t_0, \mathbf{p}) &= \mathbf{x}_0^{cv}(\mathbf{p}) \\ \dot{\mathbf{x}}^{cc}(t, \mathbf{p}) &= \mathbf{f}^{cc}(t, \mathbf{p}, \mathbf{x}^{cv}(t, \mathbf{p}), \mathbf{x}^{cc}(t, \mathbf{p})), & \mathbf{x}^{cc}(t_0, \mathbf{p}) &= \mathbf{x}_0^{cc}(\mathbf{p}) \end{aligned}$$

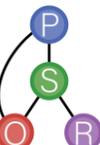
- Development of interval-based differential inequality [10,11]
- Less expansive convex/concave relaxations as well as tighter interval bounds [12,13,14]
- Adaptation of these methods to semi-explicit index-one differential-algebraic systems of equations DAEs [15,16,17]
- Methods of tightening state relaxations by exploiting model redundancy and nonlinear invariants [18,19].

## Discretize-then-Relax

$$\mathbf{x}(\tau_{q+1}, \mathbf{p}) \in \underbrace{\mathbf{x}(\tau_q, \mathbf{p}) + \sum_{j=1}^p \frac{h^j}{j!} \mathbf{f}^{(j)}(\mathbf{x}(\tau_q, \mathbf{p}), \mathbf{p})}_{\text{Taylor Series}} + \underbrace{\frac{h^{p+1}}{(p+1)!} \mathbf{f}^{(p+1)}(\mathbf{X}(\tau_q), \mathbf{P})}_{\text{Remainder Bound}}$$

- First introduced by Moore [20] based on simple existence test.
- Generalized to two step methods consisting of an existence and uniqueness test and subsequent contraction [21,22].
- Discretize-and-relax approaches with McCormick relaxations [23]
- Taylor-Interval [24], Taylor-McCormick [25] models, and Taylor-Ellipsoid [26] models were introduced which enclosure the remainder term using different set-valued arithmetic.

10. Harrison, Gary W. **Dynamic models with uncertain parameters.** *Proceedings of the first international conference on mathematical modeling. Vol. 1.* University of Missouri Rolla, 1977.
11. W. Walter. **Differential and integral inequalities.** Springer-Verlag, New York (1970)
12. Scott, Joseph K., and Paul I. Barton. **Improved relaxations for the parametric solutions of ODEs using differential inequalities.** *Journal of Global Optimization* 57.1 (2013): 143-176.
13. Scott, Joseph K., and Paul I. Barton. **Bounds on the reachable sets of nonlinear control systems.** *Automatica* 49.1 (2013): 93-100.
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16. Scott, Joseph K., and Paul I. Barton. **Interval bounds on the solutions of semi-explicit index-one DAEs. Part 2: computation.** *Numerische Mathematik* 125.1 (2013): 27-60.
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18. Shen, Kai, and Joseph K. Scott. **Rapid and accurate reachability analysis for nonlinear dynamic systems by exploiting model redundancy.** *Computers & Chemical Engineering* 106 (2017): 596-608.
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21. Berz, Martin, and Georg Hoffstätter. **Computation and application of Taylor polynomials with interval remainder bounds.** *Reliable Computing* 4.1 (1998): 83-97.
22. Nedialkov, Nedialko S., Kenneth R. Jackson, and George F. Corliss. **Validated solutions of initial value problems for ordinary differential equations.** *Applied Mathematics and Computation* 105.1 (1999): 21-68.
23. Sahlodin, Ali M., and Benoit Chachuat. **Discretize-then-relax approach for convex/concave relaxations of the solutions of parametric ODEs.** *Applied Numerical Mathematics* 61.7 (2011): 803-820.
24. Berz, Martin, and Georg Hoffstätter. **Computation and application of Taylor polynomials with interval remainder bounds.** *Reliable Computing* 4.1 (1998): 83-97.
25. Sahlodin, Ali Mohammad, and Benoit Chachuat. **Convex/concave relaxations of parametric ODEs using Taylor models.** *Computers & Chemical Engineering* 35.5 (2011): 844-857.
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# Prior Work: Stiff Systems and Global Optimization



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FUTURES ISSUE: PROCESS SYSTEMS ENGINEERING

Global optimization of stiff dynamical systems

Matthew E. Wilhelm<sup>1</sup> | Anne V. Le<sup>2</sup> | Matthew D. Stuber<sup>1</sup>

<sup>1</sup>Process Systems and Operations Research Laboratory, Department of Chemical and Biomolecular Engineering, University of Connecticut, Storrs, Mansfield, Connecticut  
<sup>2</sup>Department of Chemical Engineering, Texas A&M University, College Station, Texas

**Abstract**  
We present a deterministic global optimization method for nonlinear programming formulations constrained by stiff systems of ordinary differential equation (ODE) initial value problems (IVPs). The examples arise from dynamic optimization problems exhibiting both fast and slow transient phenomena commonly encountered in process systems engineering. The developed methods enable the guaranteed global solution of dynamic optimization problems with stiff ODE-IVPs embedded.

**KEYWORDS**  
dynamic simulation, global optimization, implicit functions, stiff systems

**1 | INTRODUCTION**  
Dynamic optimization problems of the form

$$\phi^* = \min_{\mathbf{p} \in \mathcal{P}} \phi(\mathbf{x}(\mathbf{p}, t_f), \mathbf{p})$$

program, in general, and therefore verifying optimality requires deterministic global optimization. The focus of this paper is on solving (1) to guaranteed global optimality (or declaration of infeasibility). The methods developed in this work are of specific importance when the ODE-IVP system is stiff. Methods for solving (1) rigorously to global optimality rely on the

Wilhelm, ME; Le, AV; and Stuber. MD. "Global Optimization of Stiff Dynamical Systems." *AICHE Journal: Futures Issue*, 65 (12), 2019

(Implicit Euler<sup>27,28</sup>)

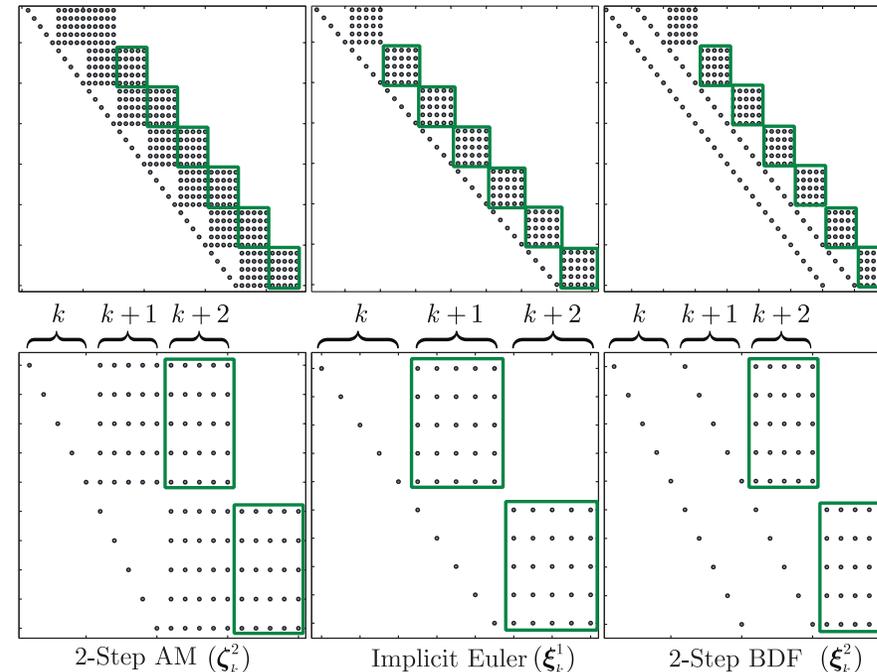
(Two-step Adam-Moulton<sup>27,28</sup>)

(Two-step BDF<sup>27,28</sup>)

$$\xi_k^1 \equiv \hat{\mathbf{z}}_{k+1} - \hat{\mathbf{z}}_k - \Delta t \mathbf{f}(\hat{\mathbf{z}}_{k+1}, \mathbf{p})$$

$$\xi_k^2 \equiv \hat{\mathbf{z}}_{k+2} - \frac{4}{3} \hat{\mathbf{z}}_{k+1} + \frac{1}{3} \hat{\mathbf{z}}_k - \frac{2}{3} \Delta t \mathbf{f}(\hat{\mathbf{z}}_{k+2}, \mathbf{p})$$

$$\xi_k^2 \equiv \hat{\mathbf{z}}_{k+2} - \hat{\mathbf{z}}_{k+1} - \frac{1}{2} \Delta t (\mathbf{f}(\hat{\mathbf{z}}_{k+2}, \mathbf{p}) + \mathbf{f}(\hat{\mathbf{z}}_{k+1}, \mathbf{p}))$$



27. Gautschi W. **Numerical Analysis**. Springer Science & Business Media, New York; 2012.  
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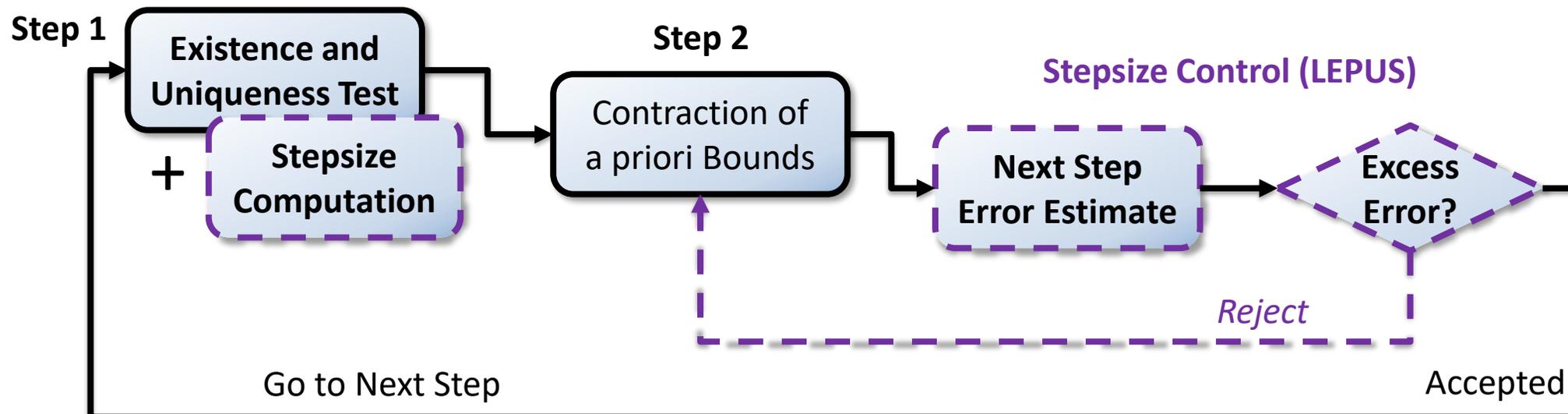


# Integration Scheme



- Discretize-then-relax algorithm employed.
- Higher-order existence test used<sup>22,29</sup>.
- Local error per unit step (LEPUS) adaptive step-size control scheme used<sup>30</sup>.
- **Step 1:** Determines step-size and state relaxations for the **entire** step ( $t \in [t_j, t_{j+1}]$ )<sup>22,30</sup>.
- **Step 2:** Refines state relaxations at new time ( $t = t_{j+1}$ ).

22. Sahlodin, Ali M., and Benoit Chachuat. **Discretize-then-relax approach for convex/concave relaxations of the solutions of parametric ODEs.** *Applied Numerical Mathematics* 61.7 (2011): 803-820.
29. Nedialkov, Nedialko S., Kenneth R. Jackson, and John D. Pryce. **An effective high-order interval method for validating existence and uniqueness of the solution of an IVP for an ODE.** *Reliable Computing* 7.6 (2001): 449-465.
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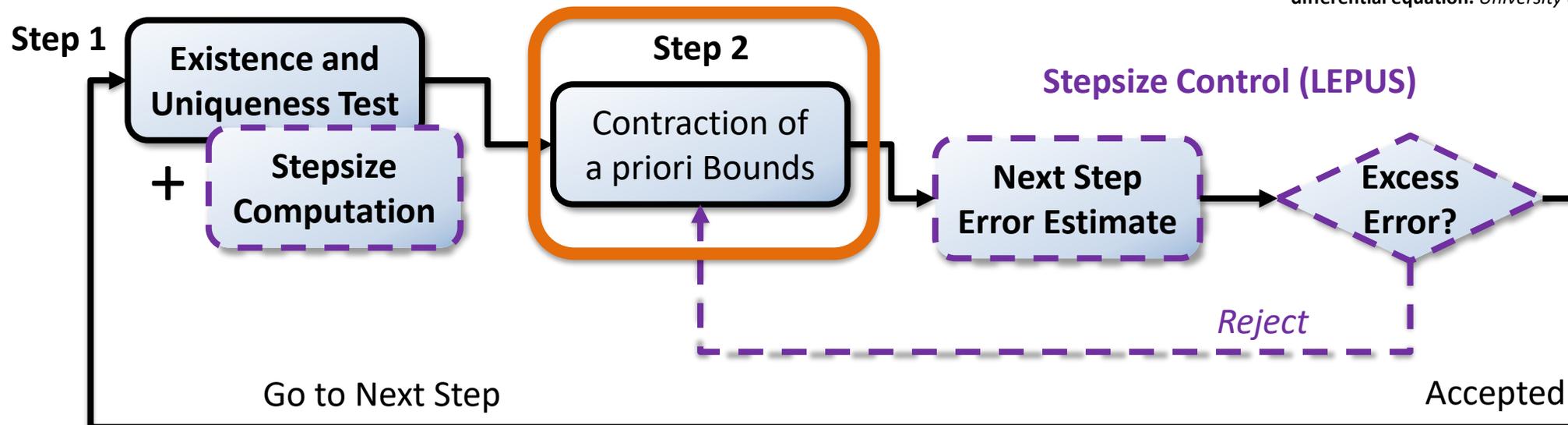


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# Adams-Moulton: Pointwise



## Adams-Moulton Method<sup>27,28</sup>

$$\mathbf{x}(\mathbf{p}, t_k) = \mathbf{x}(\mathbf{p}, t_{k-1}) + h \sum_{j=0}^n \bar{\beta}_{jn} \mathbf{f}(\mathbf{x}(\mathbf{p}, t_{k-j}), \mathbf{p})$$

$$t_{k-n}, \dots, t_k \in [t_{k-n}, t_k]$$

## Nonlinear System of Equations

$$\mathbf{h}(\mathbf{z}(\mathbf{p}), \mathbf{p}) = \mathbf{x}(\mathbf{p}, t_k) - \mathbf{x}(\mathbf{p}, t_{k-1}) - h \sum_{j=0}^n \bar{\beta}_{jn} \mathbf{f}(\mathbf{x}(\mathbf{p}, t_{k-j}), \mathbf{p}) = \mathbf{0}$$

$$\mathbf{z}(\mathbf{p}) = [\mathbf{x}(\mathbf{p}, t_k); \mathbf{x}(\mathbf{p}, t_{k-1}); \dots; \mathbf{x}(\mathbf{p}, t_{k-n})]$$

- A n-step Adams-Moulton arises from a Lagrange interpolation polynomial approximating the solution at n+1 points,  $t_{k-n}, \dots, t_k$ , in the time interval  $[t_{k-n}, t_k]$ <sup>27,28</sup>.
- These methods exhibit preferable regions of stability for stiff systems when compared with many explicit methods<sup>27,28</sup>.

## Truncation Error<sup>31</sup> ( $\tau$ )

$$\tau(\mathbf{p}, \bar{\eta}) = h^{n+1} \bar{\gamma}_{n+1} \mathbf{x}^{(n+2)}(\mathbf{p}, \bar{\eta})$$

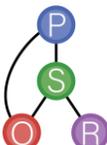
$$\tau(\mathbf{p}, \bar{\eta}) = h^{n+1} \bar{\gamma}_{n+1} \mathbf{f}^{(n+1)}(\mathbf{x}(\mathbf{p}, \bar{\eta}), \mathbf{p})$$

$$\exists \bar{\eta} \in [t_{k-n}, t_k]$$

27. Gautschi W. **Numerical Analysis**. Springer Science & Business Media, New York; 2012.

28. Hairer E, Wanner G. **Solving Ordinary Differential Equations II: Stiff and Differential-Algebraic Problems**. Springer, Heidelberg; 1991.

31. Marciniak, Andrzej, Malgorzata A. Jankowska, and Tomasz Hoffmann. **On interval predictor-corrector methods**. *Numerical Algorithms* 75.3 (2017): 777-808.



# Adams-Moulton: Pointwise



Adams-Moulton Method<sup>27,28</sup>

Truncation Error<sup>31</sup> ( $\tau$ )

- Compute relaxation for **truncation error** in standard manner
- Compute relaxation of implicit function using approach of Stuber et al. 2015<sup>32</sup> and Wilhelm et al. 2019<sup>6</sup>.

$$\tau = h^{n+1} \bar{\gamma}_{n+1} \mathbf{x}^{(n+2)}(\mathbf{p}, \bar{\eta})$$

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- 6. Wilhelm, ME; Le, AV; and Stuber, MD. **Global Optimization of Stiff Dynamical Systems**. *AIChE Journal: Futures Issue*, 65 (12), 2019
- 32. Stuber, Matthew D., Joseph K. Scott, and Paul I. Barton. **Convex and concave relaxations of implicit functions**. *Optimization Methods and Software* 30.3 (2015): 424-460.

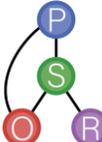
$$\mathbf{h}(\mathbf{z}(\mathbf{p}), \mathbf{p}) = \mathbf{x}(\mathbf{p}, t_k) - \mathbf{x}(\mathbf{p}, t_{k-1}) - h \sum_{j=0}^n \bar{\beta}_{jn} \mathbf{f}(\mathbf{x}(\mathbf{p}, t_{k-j}), \mathbf{p}) = 0$$

*Nonlinear System of Equations (Defining implicit function)*

$$\mathbf{h}(\mathbf{z}(\mathbf{p}), \mathbf{p}) = \mathbf{x}(\mathbf{p}, t_k) - \mathbf{x}(\mathbf{p}, t_{k-1}) - h \sum_{j=0}^n \bar{\beta}_{jn} \mathbf{f}(\mathbf{x}(\mathbf{p}, t_{k-j}), \mathbf{p}) + \tau(\mathbf{p}, \bar{\eta}) = \mathbf{0}$$

$$\mathbf{z}(\mathbf{p}) = [\mathbf{x}(\mathbf{p}, t_k); \mathbf{x}(\mathbf{p}, t_{k-1}); \dots; \mathbf{x}(\mathbf{p}, t_{k-n})]$$

...al Analysis. Springer Science  
New York; 2012.  
Solving Ordinary Differential  
and Differential-Algebraic  
Heidelberg; 1991.  
Malgorzata A. Jankowska, and  
in interval predictor-  
Numerical Algorithms 75.3



# Adams-Moulton: Mean Value Form



Mean value form of n-step Adams-Moulton method

$$\begin{aligned}
 \mathbf{x}_k = & \underbrace{\hat{\mathbf{x}}_{k-1} + h \sum_{j=0}^n \bar{\beta}_{jn} \mathbf{f}(\hat{\mathbf{x}}_{k-j}, \hat{\mathbf{p}})}_{\mathbf{D}_k(\mathbf{p})} + \underbrace{\mathbf{R}_k(\mathbf{p})}_{\text{truncation error}} + \underbrace{\sum_{j=0}^n h \bar{\beta}_{jn} \frac{\partial \mathbf{f}}{\partial \mathbf{p}}(\boldsymbol{\mu}_{k-j}(\mathbf{p}), \boldsymbol{\rho}(\mathbf{p})) (\mathbf{p} - \hat{\mathbf{p}})}_{\mathbf{J}_p^k(\mathbf{p})} \\
 & + \underbrace{\left( \mathbf{I} + h \bar{\beta}_{1n} \frac{\partial \mathbf{f}}{\partial \mathbf{x}_{k-1}}(\boldsymbol{\mu}_{k-1}(\mathbf{p}), \boldsymbol{\rho}(\mathbf{p})) \right)}_{\mathbf{I} + \mathbf{J}_x^{k-1}(\mathbf{p})} (\mathbf{x}_{k-1} - \hat{\mathbf{x}}_{k-1}) + \sum_{\substack{j=0 \\ j \neq 1}}^n h \bar{\beta}_{jn} \underbrace{\frac{\partial \mathbf{f}}{\partial \mathbf{x}_{k-j}}(\boldsymbol{\mu}_{k-j}(\mathbf{p}), \boldsymbol{\rho}(\mathbf{p}))}_{\mathbf{J}_x^{k-j}(\mathbf{p})} (\mathbf{x}_{k-j} - \hat{\mathbf{x}}_{k-j})
 \end{aligned}$$

Were we define  $\boldsymbol{\mu}_k$  and  $\boldsymbol{\rho}$  as below

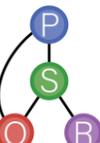
$$\boldsymbol{\mu}_k(\mathbf{p}) = \eta(\mathbf{x}_k - \hat{\mathbf{x}}_k) + \hat{\mathbf{x}}_k$$

$$\boldsymbol{\rho}(\mathbf{p}) = \eta(\mathbf{p} - \hat{\mathbf{p}}) + \mathbf{p}$$

$$\eta \in [0, 1]$$

Truncation error notation and form

$$\mathbf{R}_k(\mathbf{p}) = h^{n+2} \bar{\gamma}_{n+1} \mathbf{f}^{(n+1)}(\tilde{\mathbf{x}}(\mathbf{p}, t_{k-n}; t_k), \mathbf{p})$$



# Adams-Moulton: Interval



**Mean value form** of n-step Adams-Moulton method

$$\mathbf{x}_k = \mathbf{D}_k(\mathbf{p}) + \mathbf{J}_p^k(\mathbf{p})(\mathbf{p} - \hat{\mathbf{p}}) + \left(\mathbf{I} + \mathbf{J}_x^{k-1}(\mathbf{x}_{k-1}, \mathbf{p})\right) (\mathbf{x}_{k-1} - \hat{\mathbf{x}}_{k-1}) + \sum_{\substack{j=0 \\ j \neq 1}}^n \mathbf{J}_x^{k-j}(\mathbf{x}_{k-j}, \mathbf{p})(\mathbf{x}_{k-j} - \hat{\mathbf{x}}_{k-j})$$

**Interval bounds** of n-step Adams-Moulton method

$$\mathbf{X}_k = \mathbf{D}_k(\mathbf{P}) + \mathbf{J}_p^k(\mathbf{P})(\mathbf{P} - \hat{\mathbf{p}}) + \left(\mathbf{I} + \mathbf{J}_x^{k-1}(\mathbf{X}_{k-1}, \mathbf{P})\right) (\mathbf{X}_{k-1} - \hat{\mathbf{x}}_{k-1}) + \sum_{j=2}^n \mathbf{J}_x^{k-j}(\mathbf{X}_{k-j}, \mathbf{P})(\mathbf{X}_{k-j} - \hat{\mathbf{x}}_{k-j}) + \mathbf{J}_x^k(\mathbf{X}_k, \mathbf{P})(\mathbf{X}_k^0 - \mathbf{x}_k^0)$$

□ Uncertain set is propagated as a parallelepiped<sup>22,33</sup>.

□ Namely, that there exist  $\mathbf{A}_k \in \mathbb{R}^{n_x \times n_x}$  and  $\delta_k \in \Delta_k$  such that  $\mathbf{x}_k(\mathbf{p}) - \hat{\mathbf{x}}_k = \mathbf{A}_k \delta_k \in \mathbf{A}_k \Delta_k$ .

$$\mathbf{X}_k := \left( \mathbf{D}_k(\mathbf{P}) + \mathbf{J}_p^k(\mathbf{P})(\mathbf{P} - \hat{\mathbf{p}}) + \left(\mathbf{I} + \mathbf{J}_x^{k-1}(\mathbf{P})\right) \mathbf{A}_{k-1} \Delta_{k-1} + \sum_{j=2}^n \mathbf{J}_x^{k-j}(\mathbf{X}_{k-j}, \mathbf{P}) \mathbf{A}_{k-j} \Delta_{k-j} + \mathbf{J}_x^k(\mathbf{X}_k^0, \mathbf{P})(\mathbf{X}_k^0 - \hat{\mathbf{x}}_k^0) \right) \cap \mathbf{X}_k^0$$

22. Sahlodin, Ali M., and Benoit Chachuat. **Discretize-then-relax approach for convex/concave relaxations of the solutions of parametric ODEs.** *Applied Numerical Mathematics* 61.7 (2011): 803-820.

33. Lohner, Rudolf J. **Computation of guaranteed enclosures for the solutions of ordinary initial and boundary value problems.** *Institute of mathematics and its applications conference series.* Vol. 39. Oxford University Press, 1992.



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$$\mathbf{x}_k = \mathbf{D}_k(\mathbf{p}) + \mathbf{J}_p^k(\mathbf{p})(\mathbf{p} - \hat{\mathbf{p}}) + \left( \mathbf{I} + \mathbf{J}_x^{k-1}(\mathbf{x}_{k-1}, \mathbf{p}) \right) (\mathbf{x}_{k-1} - \hat{\mathbf{x}}_{k-1}) + \sum_{\substack{j=0 \\ j \neq 1}}^n \mathbf{J}_x^{k-j}(\mathbf{x}_{k-j}, \mathbf{p})(\mathbf{x}_{k-j} - \hat{\mathbf{x}}_{k-j})$$

Interval bounds of n-step Adams-Moulton method

$$\mathbf{X}_k = \mathbf{D}_k(P) + \mathbf{J}_p^k(P)(P - \hat{P}) + \left( \mathbf{I} + \mathbf{J}_x^{k-1}(X_{k-1}, P) \right) (X_{k-1} - \hat{X}_{k-1}) + \sum_{j=2}^n \mathbf{J}_x^{k-j}(X_{k-j}, P)(X_{k-j} - \hat{X}_{k-j}) + \mathbf{J}_x^k(X_k, P)(X_k^0 - \mathbf{x}_k^0)$$

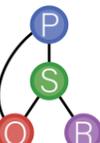
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$$X_k := \left( \mathbf{D}_k(P) + \mathbf{J}_p^k(P)(P - \hat{P}) + \left( \mathbf{I} + \mathbf{J}_x^{k-1}(P) \right) \mathbf{A}_{k-1} \Delta_{k-1} + \sum_{j=2}^n \mathbf{J}_x^{k-j}(X_{k-j}, P) \mathbf{A}_{k-j} \Delta_{k-j} + \mathbf{J}_x^k(X_k^0, P)(X_k^0 - \hat{\mathbf{x}}_k^0) \right) \cap X_k^0$$

22. Sahlodin, Ali M., and Benoit Chachuat. **Discretize-then-relax approach for convex/concave relaxations of the solutions of parametric ODEs.** *Applied Numerical Mathematics* 61.7 (2011): 803-820.

33. Lohner, Rudolf J. **Computation of guaranteed enclosures for the solutions of ordinary initial and boundary value problems.** *Institute of mathematics and its applications conference series.* Vol. 39. Oxford University Press, 1992.



# Adams-Moulton: Interval



## Initialization for parallelepiped<sup>22,33</sup>

$$\mathbf{A}_0 = \mathbf{I} \quad \Delta_0 = X_0 - \hat{\mathbf{x}}_0$$

## Parallelepiped update at step k

$\mathbf{A}_k$  update given by taking to be orthogonal matrix Q of QR decomposition of  $\text{mid}(\mathbf{J}_X^k \mathbf{A}_{k-1})$ <sup>22,33</sup>

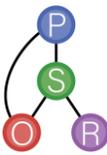
$$\Delta_k = \mathbf{A}_k^{-1} \left( D_k(P) + \mathbf{J}_P^k(P)(P - \hat{p}) + (\mathbf{I} + \mathbf{J}_X^{k-1}(P)) \mathbf{A}_{k-1} \Delta_{k-1} + \sum_{j=2}^n \mathbf{J}_X^{k-j}(X_k, P) \mathbf{A}_{k-j} \Delta_{k-j} + \mathbf{J}_X^k(X_k, P)(X_k - \hat{\mathbf{x}}_k) \right)$$

22. Sahlodin, Ali M., and Benoit Chachuat. **Discretize-then-relax approach for convex/concave relaxations of the solutions of parametric ODEs.** *Applied Numerical Mathematics* 61.7 (2011): 803-820.

33. Lohner, Rudolf J. **Computation of guaranteed enclosures for the solutions of ordinary initial and boundary value problems.** *Institute of mathematics and its applications conference series*. Vol. 39. Oxford University Press, 1992.

## Bound truncation error via partition

$$R_k(P) \equiv h^{n+2} \bar{\gamma}_{n+1} \bigcup_{j=0}^n F^{(n+1)}(\tilde{X}_{k-j}, P) \subseteq h^{n+2} \bar{\gamma}_{n+1} F^{(n+1)} \left( \bigcup_{j=0}^n \tilde{X}_{k-j}, P \right)$$



# Adams-Moulton: Interval



Initialization for parallelepiped<sup>22,33</sup>

$$\mathbf{A}_0 = \mathbf{I} \quad \Delta_0 = \mathbf{X}_0 - \hat{\mathbf{x}}_0$$

Parallelepiped update at step k

$\mathbf{A}_k$  update given by taking to be orthogonal matrix Q of QR decomposition of  $\text{mid}(\mathbf{J}_x^k \mathbf{A}_{k-1})$ <sup>22,33</sup>

$$\Delta_k = \mathbf{A}_k^{-1} \left( \mathbf{D}_k(\mathbf{P}) + \mathbf{J}_p^k(\mathbf{P})(\mathbf{P} - \hat{\mathbf{p}}) + \left( \mathbf{I} + \mathbf{J}_x^{k-1}(\mathbf{P}) \right) \mathbf{A}_{k-1} \Delta_{k-1} + \sum_{j=2}^n \mathbf{J}_x^{k-j}(\mathbf{X}_k, \mathbf{P}) \mathbf{A}_{k-j} \Delta_{k-j} + \mathbf{J}_x^k(\mathbf{X}_k, \mathbf{P})(\mathbf{X}_k - \hat{\mathbf{x}}_k) \right)$$

22. Sahlodin, Ali M., and Benoit Chachuat. Discretize-then-relax approach for convex/concave relaxations of the solutions of parametric ODEs. *Applied Numerical Mathematics* 61.7 (2011): 803-820.

33. Lohner, Rudolf J. *Computation of guaranteed enclosures for the solutions of ordinary initial and boundary value problems. Institute of mathematics and its applications conference series.* Vol. 39. Oxford University Press, 1992.

**Bound truncation error via partition**

$$\mathbf{R}_k(\mathbf{P}) \equiv h^{n+2} \bar{\gamma}_{n+1} \bigcup_{j=0}^n \mathbf{F}^{(n+1)}(\tilde{\mathbf{X}}_{k-j}, \mathbf{P}) \subseteq h^{n+2} \bar{\gamma}_{n+1} \mathbf{F}^{(n+1)} \left( \bigcup_{j=0}^n \tilde{\mathbf{X}}_{k-j}, \mathbf{P} \right)$$



# Adams-Moulton: Relaxation



**Interval update** of n-step Adams-Moulton method

$$X_k := \left( D_k(P) + \mathbf{J}_p^k(P)(P - \hat{\mathbf{p}}) + \left( \mathbf{I} + \mathbf{J}_x^{k-1}(P) \right) \mathbf{A}_{k-1} \Delta_{k-1} + \sum_{j=2}^n \mathbf{J}_x^{k-j}(X_{k-j}, P) \mathbf{A}_{k-j} \Delta_{k-j} + \mathbf{J}_x^k(X_k^0, P)(X_k^0 - \mathbf{x}_k^0) \right) \cap X_k^0$$

**Convex/concave relaxation update** of n-step Adams-Moulton method

Let  $\{\mathbf{g}^{\text{cv}}, \mathbf{g}^{\text{cc}}\}(\mathbf{p})$  denote the tuple of convex and concave relaxations of  $\mathbf{g}$  on  $P$  evaluated at  $\mathbf{p} \in P$ :

$$\begin{aligned} \{\mathbf{x}_k^{\text{cv}}, \mathbf{x}_k^{\text{cc}}\}(\mathbf{p}) &:= \{\mathbf{D}_k^{\text{cv}}, \mathbf{D}_k^{\text{cc}}\}(\mathbf{p}) + \{\mathbf{J}_p^{\text{cv}}, \mathbf{J}_p^{\text{cc}}\}(\mathbf{p})(\mathbf{p} - \hat{\mathbf{p}}) + \left( \mathbf{I} + \{\mathbf{J}_x^{k-1, \text{cv}}, \mathbf{J}_x^{k-1, \text{cc}}\}(\mathbf{p}) \right) \otimes \mathbf{A}_{k-1} \{\Delta_{k-1}^{\text{cv}}, \Delta_{k-1}^{\text{cc}}\}(\mathbf{p}) \\ &\quad + \sum_{j=2}^n \{\mathbf{J}_x^{k-j, \text{cv}}, \mathbf{J}_x^{k-j, \text{cc}}\}(\mathbf{p}) \mathbf{A}_{k-j} \{\Delta_{k-j}^{\text{cv}}, \Delta_{k-j}^{\text{cc}}\}(\mathbf{p}) \{\mathbf{J}_x^{\text{cv}}, \mathbf{J}_x^{\text{cc}}\}(\mathbf{p}) (\{\mathbf{x}_k^{0, \text{cv}}, \mathbf{x}_k^{0, \text{cc}}\}(\mathbf{p}) - \hat{\mathbf{x}}_k^0) \end{aligned}$$

$$\{\mathbf{x}_k^{\text{cv}}, \mathbf{x}_k^{\text{cc}}\}(\mathbf{p}) := \text{intersect}(\{\mathbf{x}_k^{\text{cv}}, \mathbf{x}_k^{\text{cc}}\}(\mathbf{p}), X_k^0)$$



# Adams-Moulton: Relaxation



## Generalization of Union:

Compute union  $(\{\mathbf{x}_k^{cv}, \mathbf{x}_k^{cc}\}(\mathbf{p}), \{\mathbf{x}_k^{0,cv}, \mathbf{x}_k^{0,cc}\}(\mathbf{p}))$  and update  $\{\mathbf{x}_k^{cv}, \mathbf{x}_k^{cc}\}(\mathbf{p})$  as follows:

$$\text{Step 1: } \{\boldsymbol{\varphi}_l^{cv}, \boldsymbol{\varphi}_l^{cc}\}(\mathbf{p}) \leftarrow \min(\{\mathbf{x}_k^{cv}, \mathbf{x}_k^{cc}\}(\mathbf{p}), \{\mathbf{x}_k^{0,cv}, \mathbf{x}_k^{0,cc}\}(\mathbf{p}))$$

$$\text{Step 2: } \{\boldsymbol{\varphi}_u^{cv}, \boldsymbol{\varphi}_u^{cc}\}(\mathbf{p}) \leftarrow \max(\{\mathbf{x}_k^{cv}, \mathbf{x}_k^{cc}\}(\mathbf{p}), \{\mathbf{x}_k^{0,cv}, \mathbf{x}_k^{0,cc}\}(\mathbf{p}))$$

$$\text{Step 3: } \{\mathbf{x}_k^{cv}, \mathbf{x}_k^{cc}\}(\mathbf{p}) \leftarrow : \{\boldsymbol{\varphi}_l^{cv}, \boldsymbol{\varphi}_u^{cc}\}(\mathbf{p})$$

Pairwise composite relaxations  
of min/max evaluated by  
McCormick arithmetic

## Bound truncation error via partition

$$\{\mathbf{R}_k^{cv}, \mathbf{R}_k^{cc}\}(\mathbf{p}) = h^{n+2} \bar{\gamma}_{n+1} \text{union} \left( \text{union}(\mathbf{f}^{(n+1)}(\{\mathbf{x}_k^{cv}, \mathbf{x}_k^{cc}\}(\mathbf{p}), \mathbf{p}), \dots), \mathbf{f}^{(n+1)}(\{\mathbf{x}_{k-n}^{cv}, \mathbf{x}_{k-n}^{cc}\}(\mathbf{p}), \mathbf{p}) \right)$$

## Subgradient-based tightening of state bounds:

Update interval bounds at  $\mathbf{k}$  by using interval extension of affine relaxations compute at  $\mathbf{p}_{\text{ref}}$  if an improvement<sup>14</sup>.

22. Sahlodin, Ali M., and Benoit Chachuat. **Discretize-then-relax approach for convex/concave relaxations of the solutions of parametric ODEs.** *Applied Numerical Mathematics* 61.7 (2011): 803-820.



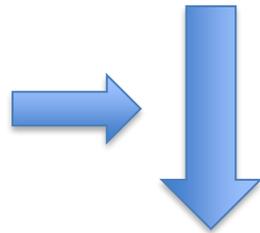
# Implementation



Customizable Global and Robust Optimization Routines



*Implicit Linear  
Multistep Relaxations*



**EAGODynamicOptimizer.jl**

- 34. Wilhelm, M. E., and M. D. Stuber. **EAGO.jl: easy advanced global optimization in Julia.** *Optimization Methods and Software* (2020): 1-26.
- 35. Bezanson, Jeff, et al. **Julia: A fresh approach to numerical computing.** *SIAM review* 59.1 (2017): 65-98.



# Implementation



## Customizable Global and Robust Optimization Routines



*Implicit Linear  
Multistep Relaxations*



**EAGODynamicOptimizer.jl**

## Abstract Layer for Dynamic Problems



- **DynamicBounds.jl** – Wrapper for dependent modules
- **DynamicBoundsBase.jl** – Abstraction Layer
- **DynamicBoundspODEsDiscrete.jl**
  - Discrete time approaches
- **DynamicBoundspODEsIneq.jl**
  - Continuous time approaches

34. Wilhelm, M. E., **DynamicBounds.jl**, (2020), GitHub repository, <https://github.com/PSORLab/DynamicBounds.jl>

35. Wilhelm, M. E., **EAGODynamicOptimizer.jl**, (2020), GitHub repository, <https://github.com/PSORLab/EAGODynamicOptimizer.jl>

36. Wilhelm, M. E., **McCormick.jl**, (2020), GitHub repository, <https://github.com/PSORLab/McCormick.jl>

37. Wilhelm, M. E., and M. D. Stuber. **EAGO. jl: easy advanced global optimization in Julia**. *Optimization Methods and Software* (2020): 1-26.

38. Bezanson, Jeff, et al. **Julia: A fresh approach to numerical computing**. *SIAM review* 59.1 (2017): 65-98.



# Implementation



## Customizable Global and Robust Optimization Routines

## Abstract Layer for Dynamic Problems

- **IntervalArithmetic.jl** for validated interval calculations.
- Relaxations from McCormick.jl<sup>36</sup> submodule of **EAGO.jl**<sup>37</sup>.
- All simulations run on single thread of Intel Xeon E3-1270 v5 3.60/4.00GHz processor with 16GM ECC RAM, Ubuntu 18.04LTS using Julia v1.5.1<sup>38</sup>. Intel MKL 2019 (Update 2) for BLAS/LAPACK.

*Implicit  
Multistep*

DynamicBounds.jl

dependent modules  
Optimization Layer

34. Wilhelm, M. E., **DynamicBounds.jl**, (2020), GitHub repository, <https://github.com/PSORLab/DynamicBounds.jl>

35. Wilhelm, M. E., **EAGODynamicOptimizer.jl**, (2020), GitHub repository, <https://github.com/PSORLab/EAGODynamicOptimizer.jl>

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38. Bezanson, Jeff, et al. **Julia: A fresh approach to numerical computing**. *SIAM review* 59.1 (2017): 65-98.



# Kinetic Problem - Formulation



(Objective Function)

$$\Phi^* = \min_{p \in P} \sum_{i=1}^n (I^i - I_{\text{data}}^i)^2$$

$$\text{s.t. } I^i = x_A^i + \frac{2}{21} x_B^i + \frac{2}{21} x_D^i$$

(Description of Problem)

- Fit the rate constants ( $k_{2f}$ ,  $k_{3f}$ ,  $k_4$ ) of oxygen addition to cyclohexadienyl radicals to data.<sup>39</sup>
- First addressed by global by Singer et al.<sup>40</sup>
- Explicit Euler form solved by Mitsos<sup>3</sup>
- Implicit Euler form addressed in Stuber<sup>32</sup>
- Two-step PILMS forms addressed in Wilhelm<sup>6</sup>

(pODE IVP)

$$\begin{aligned} \dot{x}_A &= k_1 x_Z x_Y - c_{O_2} (k_{2f} + k_{3f}) x_A + (k_{2f}/K_2) x_D + (k_{3f}/K_3) x_B - k_5 x_A^2, \\ \dot{x}_B &= k_{3f} c_{O_2} x_A - (k_{3f}/K_3 + k_4) x_B, & \dot{x}_D &= k_{2f} c_{O_2} x_A - (k_{2f}/K_2) x_D, \\ \dot{x}_Y &= -k_{1s} x_Y x_Z, & \dot{x}_Z &= -k_1 x_Y x_Z, \end{aligned}$$

(Decision Variables)

$$\mathbf{u} = (k_{2f}, k_{3f}, k_4)$$

(State Variables)

$$\mathbf{x} = (x_A, x_B, x_D, x_Y, x_Z)$$

(Parameters)

$$k_1, k_{1s}, k_5, K_2, K_3, c_{O_2}, \Delta t, n$$

(Initial Condition)

$$\dot{\mathbf{x}}(t=0) = (0, 0, 0, 0.4, 140)$$

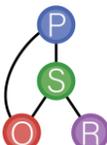
3. Mitsos et al. **McCormick-based relaxations of algorithms.** *SIAM Journal on Optimization*, SIAM (2009) 20, 73-601

6. Wilhelm, ME; Le, AV; and Stuber. MD. "Global Optimization of Stiff Dynamical Systems." *AIChE Journal: Futures Issue*, 65 (12), 2019

32. Stuber, M.D. et al. **Convex and concave relaxations of implicit functions.** *Optimization Methods and Software* (2015), 30, 424-460

39. J. W. Taylor, et al. **Direct measurement of the fast, reversible addition of oxygen to cyclohexadienyl radicals in nonpolar solvents,** *Phys. Chem. A*, 108 (2004), pp. 7193–7203.

40. A. B. Singer et al., **Global dynamic optimization for parameter estimation in chemical kinetics** A. B. Singer et al., *J. Phys. Chem. A*, 110 (2006), pp. 971–976



# Kinetic Problem - Formulation



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s. t.  $I^i =$

(Description of Problem)

➤ Fit the rate constants ( $k_{2f}$ ,  $k_{3f}$ ,  $k_4$ ) of oxygen addition to cyclohexadienyl radicals to data.<sup>39</sup>

(pODE IVP)

$$\dot{x}_A = k_1 x_A$$

$$\dot{x}_B = k_{3f} x_A x_B$$

$$\dot{x}_Y = -k_4 x_B x_Y$$

- Affine relaxations used to compute lower bound (CPLEX 12.8).
- Upper-bound computed by integrating ODE at midpoint of active node then evaluating objective & constraints.
- Duality-based bound tightening was performed in all cases.
- Absolute and relative convergence tolerances for the B&B algorithm of  $10^{-2}$  and  $10^{-5}$ , respectively.

3. Mitsos et al. *M*

6. Wilhelm, ME; Le,

32. Stuber, M.D. et al. **Convex and concave relaxations of implicit functions.** *Optimization Methods and Software* (2015), 30, 424-460

39. J. W. Taylor, et al. **Direct measurement of the fast, reversible addition of oxygen to cyclohexadienyl radicals in nonpolar solvents,** *Phys. Chem. A*, 108 (2004), pp. 7193–7203.

40. A. B. Singer et al., **Global dynamic optimization for parameter estimation in chemical kinetics** A. B. Singer et al., *J. Phys. Chem. A*, 110 (2006), pp. 971–976

( $k_1, k_2, k_3, k_4$ )

( $x_A, x_B, x_Y, x_Z$ )

( $K_3, c_{O_2}, \Delta t, n$ )

( $x_A, x_B, x_Y, x_Z, 0, 0, 0.4, 140$ )

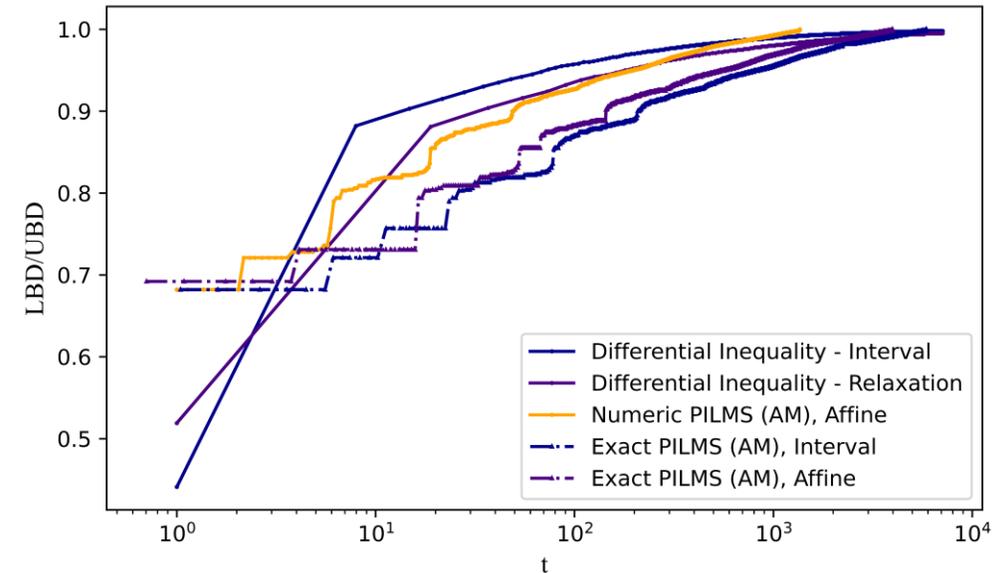


# Kinetic Problem - Results

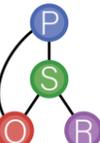


- ❑ A comparison of our new approach is made to existing methods.
- ❑ The 200 step numerical Adams-Moulton (AM, 2<sup>nd</sup> order) approach of Wilhelm 2019 is compared to the exact bounds of the solution set with the novel method.
- ❑ Differential inequality used approaches using the CVODE Adams integrator (SUNDIALS)<sup>41</sup> are included for comparison.

Method	Lower Bound	Final Relative Gap	Time (s)	Iterations
Exact PILMS, Adams-Moulton	Interval	None	5983	>800,000
Exact PILMS, Adams-Moulton	Affine	None	3976	>350,000
Numerical, Adams-Moulton, 200 step	Affine	None	1356	6068
Differential Inequality	Interval <sup>6,7,9</sup>	1.9E-3	>7200	>1,300,000



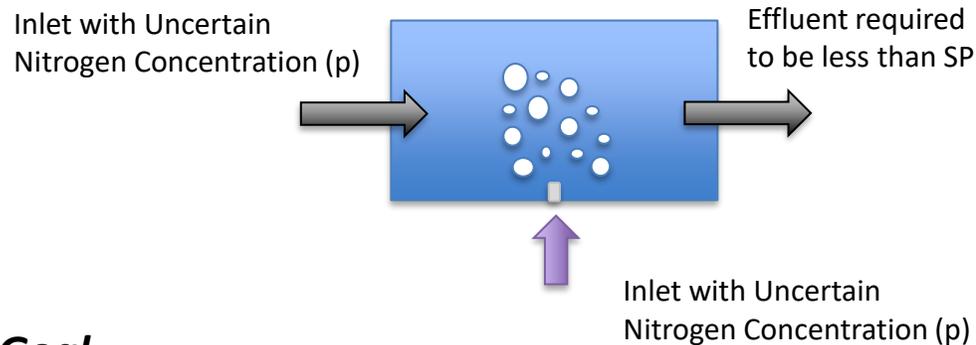
- Serban, Radu, and Alan C. Hindmarsh. **CVODES: the sensitivity-enabled ODE solver in SUNDIALS.** *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*. Vol. 47438. 2005.
- Wilhelm, ME; Le, AV; and Stuber. MD. "Global Optimization of Stiff Dynamical Systems." *AIChE Journal: Futures Issue*, 65 (12), 2019
- Harrison, Gary W. **Dynamic models with uncertain parameters.** *Proceedings of the first international conference on mathematical modeling*. Vol. 1. University of Missouri Rolla, 1977.
- W. Walter. **Differential and integral inequalities** Springer-Verlag, New York (1970)
- Scott, Joseph K., and Paul I. Barton. **Bounds on the reachable sets of nonlinear control systems.** *Automatica* 49.1 (2013): 93-100.
- Scott, Joseph K., and Paul I. Barton. **Improved relaxations for the parametric solutions of ODEs using differential inequalities.** *Journal of Global Optimization* 57.1 (2013): 143-176.



# Robust Design - SIP



## CSTR with Aeration



### Goal

Minimize aeration cost while ensuring constraint satisfaction at final time ( $t = 500$  s) if step-change feed disturbance occurs

$$\Phi^* = \min_{u \in U} u$$

$$s. t. x_1(t_f, u, p) - SP \leq 0, \forall p \in P$$

### Initial Condition

Steady-state operation with  $x_1 = 30$  (mg/L)

## Mass balance

$$\frac{dx_1}{dt} = \tau^{-1}(p - x_1) - r_{AO}X_{AO}$$

$$\frac{dx_2}{dt} = r_{AO}X_{AO} - r_{NO}(x_2, x_4)X_{NO}$$

$$\frac{dx_3}{dt} = r_{NO}(x_2, x_4)X_{NO}$$

$$\frac{dx_4}{dt} = -r_{AO}\Psi_{AO}X_{AO} - r_{NO}(x_2, x_4)\Psi_{NO}X_{NO} + ku(C_O^* - x_4)$$

## Rate Law

$$r_{NO} = r_{NO,max} \frac{x_2}{K_{SNO} + x_2 + x_2^2/K_{INO}} \frac{x_4}{K_{ONO} + x_4}$$

## Variable Range

$$P = [31,40], \quad U = [440,2000], \quad t = [0,500]$$



# Comparison of Methods



- Optimal aeration rate found to be  $u = 704 L/s$  via algorithms compared.
- Exact PILMs methods faster than numerical approximation.
- Exact PILMs comparable to differential inequality method.

Method	Lower Bound	Time (s)
Exact PILMS, Adams-Moulton	Interval	55
Exact PILMS, Adams-Moulton	Affine	36
Numerical, Adams-Moulton, 200 step	Interval	323
Numerical, Adams-Moulton, 200 step	Affine	118
Differential Inequality	Interval	38

Parameter	Value	Reference
Residence time ( $\tau$ )	4136	-
Saturated Oxygen Concentration ( $C_O^*$ )	9.1	Rodger B. Baird, Andrew D. Eaton, and Eugene W. Rice. <b>Standard Methods for the Examination of Water and Wastewater</b> . APHA, AWWA, and WEF, Washington, D.C., 2017.
Concentration of AOB ( $X_{AO}$ )	505	Omar Sánchez, et al. <b>The effect of sodium chloride on the two-step kinetics of the nitrifying process</b> . <i>Water Environment Research</i> , 76(1):73–80.
Concentration of NOB ( $X_{NO}$ )	151	
Maximum Nitrite Consumption Rate ( $r_{NO,max}$ )	1.07	
Stoichiometric ratio $O_2:NH_4$ ( $\Psi_{AO}$ )	2.5	Udo Wiesmann. <b>Biological nitrogen removal from wastewater</b> . In <i>Biotechnics / Wastewater</i> , pages 113–154. Springer Berlin Heidelberg, 1994.
Stoichiometric ratio $O_2:NO_2^-$ ( $\Psi_{NO}$ )	0.32	
Monod constant of $NO_2$ for NOB ( $K_{SNO}$ )	1.6	
Inhibition constant of $NO_2$ for NOB ( $K_{INO}$ )	13000	
Monod constant of $O_2$ for NOB ( $K_{ONO}$ )	1.5	
Lumped aeration constant (k)	3.26E-6	Lars Uby. <b>Next steps in clean water oxygen transfer testing – a critical review of current standards</b> . <i>Water Research</i> , 157:415–434, 2019.

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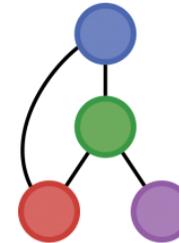
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