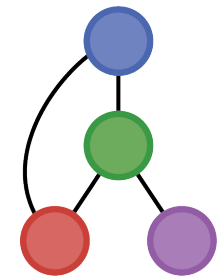


Advances in EAGO.jl: Updates, Dynamics, and Parallelism

Robert Gottlieb, PhD Student
Dimitri Alston, PhD Student
Pengfei Xu, PhD Student
Matthew Stuber, Associate Professor

November 7th, 2023

2023 / AIChE
ANNUAL
MEETING



Process Systems and
Operations Research
Laboratory

EAGO Philosophy

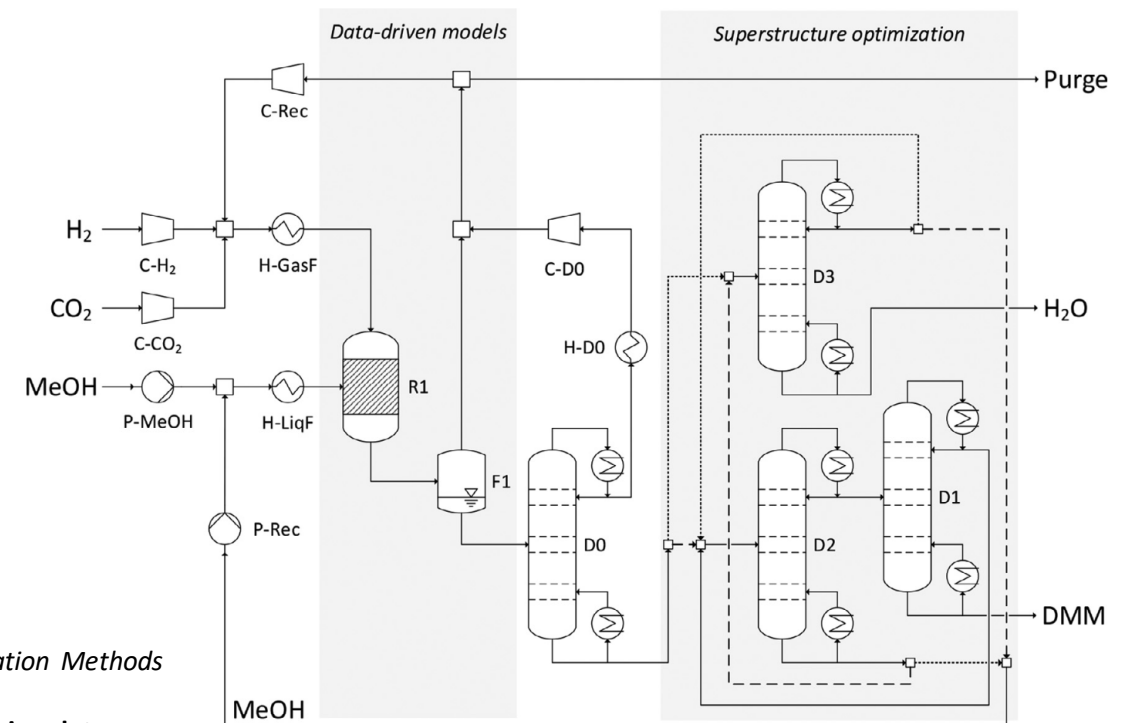
Easy Advanced Global Optimization¹



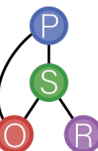
Deterministic global optimizer

- **High performance**
- **Easy to formulate** complicated problems
- **Open-source and free** for non-commercial use

1. Wilhelm, M.E., and Stuber, M.D. **EAGO.jl: easy advanced global optimization in Julia**. *Optimization Methods and Software*, (2022) **37**(2): 425-450.
2. Burre, J., et al. **Global flowsheet optimization for reductive dimethoxymethane production using data-driven thermodynamic models**. *Computers & Chemical Engineering*, (2022): 107806.



AIChE Annual Meeting 2023



EAGO Philosophy

Easy Advanced Global Optimization¹



Research Platform

- Focus on **unsolved problems**
- Designed for **user-defined functions** and custom routines
 - **Anyone** can implement and test new ideas

```
1 import EAGO: Optimizer, GlobalOptimizer
2
3 function aBB_relax(Q::Matrix{T}, c::Vector{T}, xL::Vector{T}, xU::Vector{T}, x::Real...) where {T<:Float64}
4     α=max(0, -minimum(eigvals(Q))/2)
5     y = [x[1];x[2]]
6     cv = 1/2*y'*Q*y+c'*y+α*(xL-y)'*(xU-y)
7     return cv
8 end
9
10 struct aBB_Convex <: EAGO.ExtensionType end
11 import EAGO: lower_problem!
12 > function EAGO.lower_problem!(t::aBB_Convex, opt::GlobalOptimizer) ...
63 end
```

1. Wilhelm, M.E., and Stuber, M.D. EAGO.jl: easy advanced global optimization in Julia. *Optimization Methods and Software*, (2022) 37(2): 425-450.



MINLP Example

Process parameters:

$$\hat{y}_1^{(1)}(\mathbf{x}) = 3.55 + 0.27c_1 + 0.58c_2 + 60.6x_2 - 2.8c_1x_2 - 2.3c_2x_2,$$

$$\hat{y}_1^{(2)}(\mathbf{x}, \mathbf{z}) = 126586.5 - 21466.8\hat{y}_1^{(1)}(\mathbf{x}) + 520.43x_3 + 56.29z_1 + 315.95z_2$$

$$- 43.72x_3\hat{y}_1^{(1)}(\mathbf{x}) + 3.74x_3^2 + 910.1\hat{y}_1^{(1)}(\mathbf{x})^2$$

$$- 30.6\hat{y}_1^{(1)}(\mathbf{x})z_1 - 173.17\hat{y}_1^{(1)}(\mathbf{x})z_2,$$

$$\hat{y}_1^{(3)}(\mathbf{x}, \mathbf{z}) = 9.16 + 0.092x_3 + 0.73x_4 + 0.64x_3x_4 - 0.49x_4^2 - 0.13x_4\hat{y}_1^{(2)}(\mathbf{x}, \mathbf{z})$$

$$+ 0.0019\hat{y}_1^{(2)}(\mathbf{x}, \mathbf{z})^2 + 0.018\hat{y}_1^{(2)}(\mathbf{x}, \mathbf{z}),$$

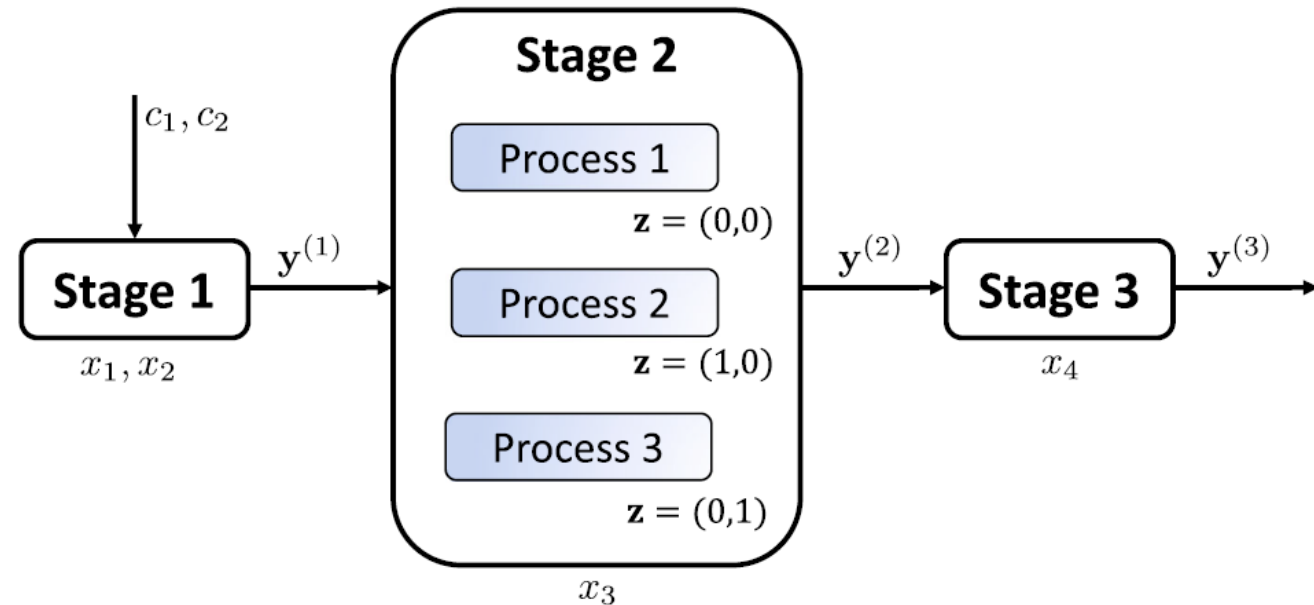
Reduced space formulation:

$$f^* = \min_{\mathbf{x} \in X, \mathbf{z} \in Z} \left(\hat{y}_1^{(3)}(\mathbf{x}, \mathbf{z}) - \eta \right)^2$$

$$\text{s.t. } z_1 + z_2 \leq 1$$

$$X = [7, 10] \times [0.1, 0.3] \times [-1.078, 1.078] \times [-1.078, 1.078]$$

$$c_1 = 0.001, \quad c_2 = 0.03$$



2. Wilhelm, M.E., & Stuber, M.D. **Improved Convex and Concave Relaxations of Composite Bilinear Forms.** *Journal of Optimization Theory and Applications*, **197** (2023): 174-204. AICHE Annual Meeting 2023



MINLP Example

Process parameters:

$$\hat{y}_1^{(1)}(\mathbf{x}) = 3.55 + 0.27c_1 + 0.58c_2 + 60.6x_2 - 2.8c_1x_2 - 2.3c_2x_2,$$

$$\begin{aligned}\hat{y}_1^{(2)}(\mathbf{x}, \mathbf{z}) = & 126586.5 - 21466.8\hat{y}_1^{(1)}(\mathbf{x}) + 520.43x_3 + 56.29z_1 + 315.95z_2 \\ & - 43.72x_3\hat{y}_1^{(1)}(\mathbf{x}) + 3.74x_3^2 + 910.1\hat{y}_1^{(1)}(\mathbf{x})^2 \\ & - 30.6\hat{y}_1^{(1)}(\mathbf{x})z_1 - 173.17\hat{y}_1^{(1)}(\mathbf{x})z_2,\end{aligned}$$

$$\begin{aligned}\hat{y}_1^{(3)}(\mathbf{x}, \mathbf{z}) = & 9.16 + 0.092x_3 + 0.73x_4 + 0.64x_3x_4 - 0.49x_4^2 - 0.13x_4\hat{y}_1^{(2)}(\mathbf{x}, \mathbf{z}) \\ & + 0.0019\hat{y}_1^{(2)}(\mathbf{x}, \mathbf{z})^2 + 0.018\hat{y}_1^{(2)}(\mathbf{x}, \mathbf{z}),\end{aligned}$$

Reduced space formulation:

$$f^* = \min_{\mathbf{x} \in X, \mathbf{z} \in Z} \left(\hat{y}_1^{(3)}(\mathbf{x}, \mathbf{z}) - \eta \right)^2$$

$$\text{s.t. } z_1 + z_2 \leq 1$$

$$X = [7, 10] \times [0.1, 0.3] \times [-1.078, 1.078] \times [-1.078, 1.078]$$

$$c_1 = 0.001, \quad c_2 = 0.03$$

```
13 # Set up the model
14 m = Model(EAGO.Optimizer(SubSolvers(; r = GLPK.Optimizer())))
15
16 # Write out process parameters
17 c = [0.001; 0.03]
18 η = 5.0
19 y1ex = :(3.55 + 0.27*(c[1]) + 0.58*(c[2]) + 60.6*(x[2]) - 2.8*(c[1])*(x[2]) -
20         2.3*(c[2])*(x[2]))
21 y2ex = :(126585.5 - 21466*y1ex + 520.43*(x[3]) + 56.29*(z[1]) + 315.95*(z[2]) -
22         43.72*(x[3])*(y1ex) + 3.74*(x[3])^2 + 910.1*y1ex^2 - 30.6*y1ex*(z[1]) -
23         173.17*y1ex*(z[2]))
24 y3ex = :(9.16 + 0.092*(x[3]) + 0.73*(x[4]) + 0.64*(x[3])*(x[4]) - 0.49*(x[4])^2 -
25         0.13*(x[4])*y2ex + 0.0019*y2ex^2 + 0.018*y2ex)
26
27 # Define optimization problem variables
28 xL = [7.0; 0.1; -1.078; -1.078]
29 xU = [10.0; 0.3; 1.078; 1.078]
30 @variable(m, xL[i] <= x[i=1:4] <= xU[i])
31 @variable(m, z[i=1:2], Bin)
32
33 # Define constraints
34 @constraint(m, z[1] + z[2] <= 1)
35
36 # Define the objective function
37 @NLobjective(m, Min, (y3ex - η)^2)
38
39 # Optimize
40 optimize!(m)
```

2. Wilhelm, M.E., & Stuber, M.D. **Improved Convex and Concave Relaxations of Composite Bilinear Forms.** *Journal of Optimization Theory and Applications*, **197** (2023): 174-204.



Anaerobic Digestion

- U.S. wastewater treatment:
 - ~2% of energy consumption³
 - ~0.7% of greenhouse gas emissions⁴
- Both costs can be offset by utilizing **anaerobic digestion (AnD)** and a **combined heat and power (CHP)** system
- Common models of AnD are **complicated**
 - High-dimensional
 - Dynamic
 - Challenging to optimize



Photo credit: <https://glsd.org>

3. EPA. Energy efficiency for water utilities, March 2022. URL <https://www.epa.gov/sustainable-water-infrastructure/energy-efficiency-water-utilities>.

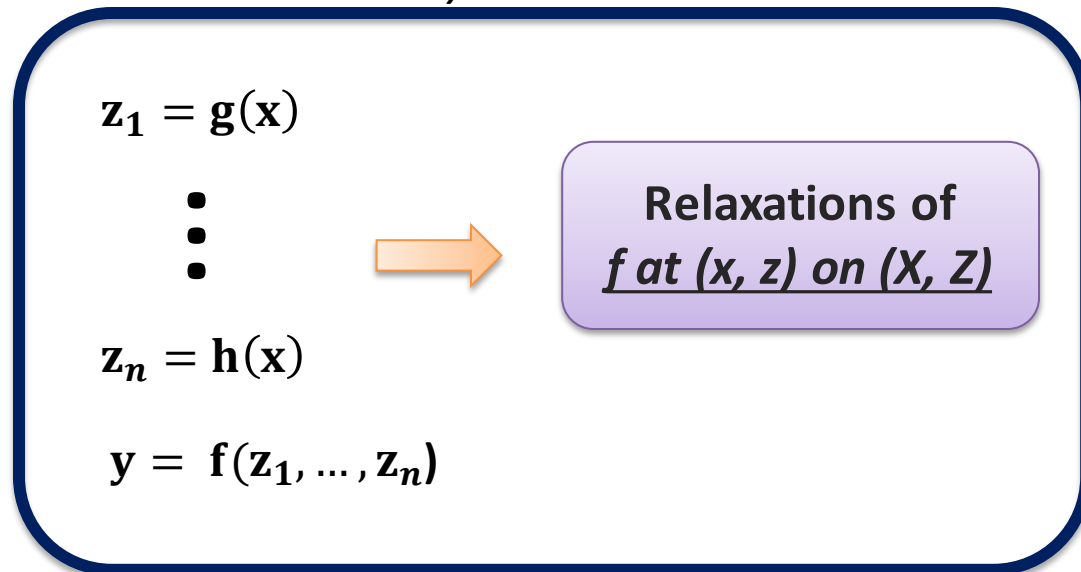
4. EPA. Inventory of U.S. greenhouse gas emissions and sinks: 1990-2020. Technical Report EPA 430-R-22-003, U.S. Environmental Protection Agency, 2022. URL <https://www.epa.gov/ghgemissions/draft-inventory-us-greenhouse-gas-emissions-and-sinks-1990-2020>.



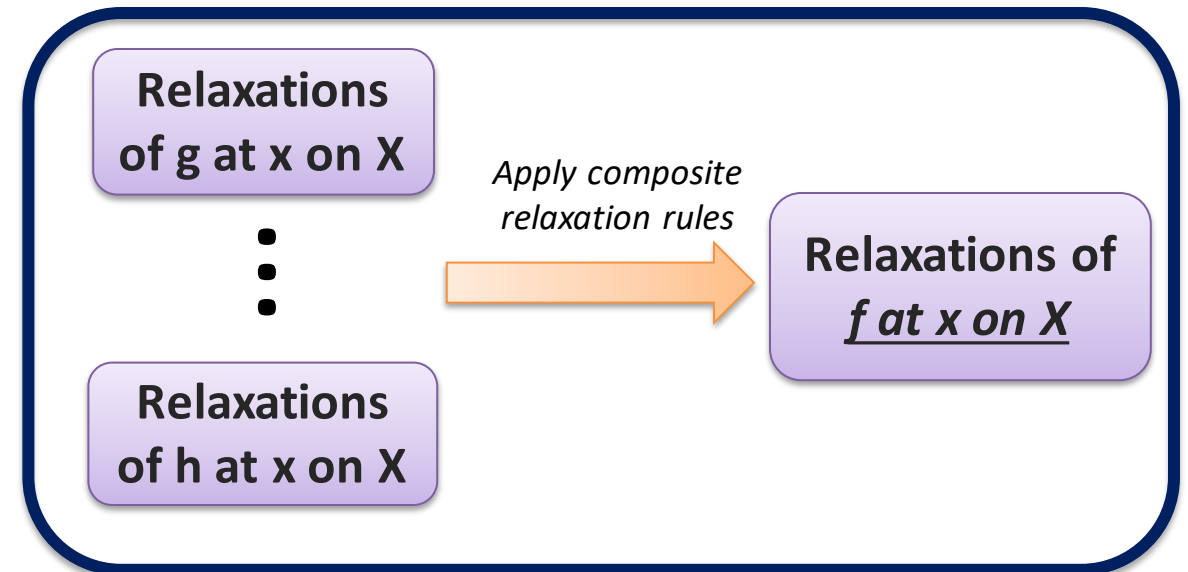
McCormick Relaxations of Factorable Functions

$$\mathbf{y} = \mathbf{f}(\mathbf{g}(\mathbf{x}), \dots, \mathbf{h}(\mathbf{x}))$$

Auxiliary Variable Method



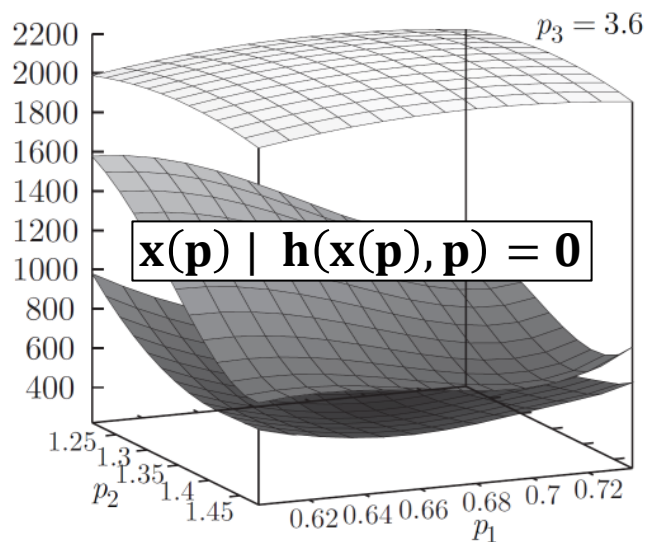
McCormick-Based Relaxations^{5,6}



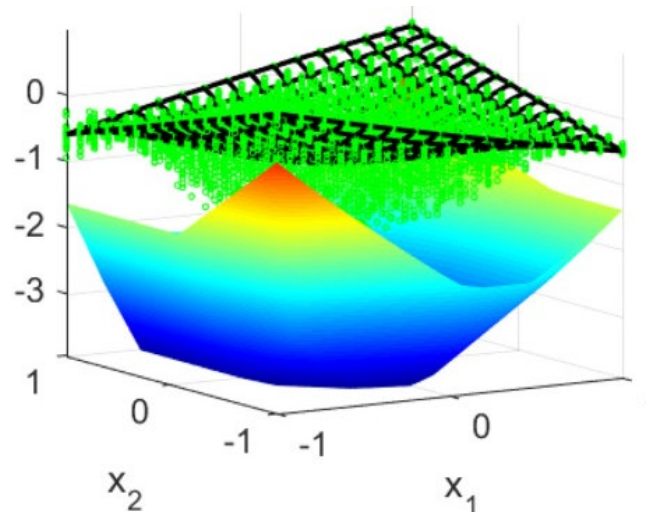
5. Mitsos, A., et al. **McCormick-based relaxations of algorithms**. *SIAM Journal on Optimization*, SIAM (2009) 20, 73-601.
6. Scott, J.K., et al. **Generalized McCormick relaxations**. *Journal of Global Optimization* 51.4 (2011): 569-606.

Reduced Space Relaxations

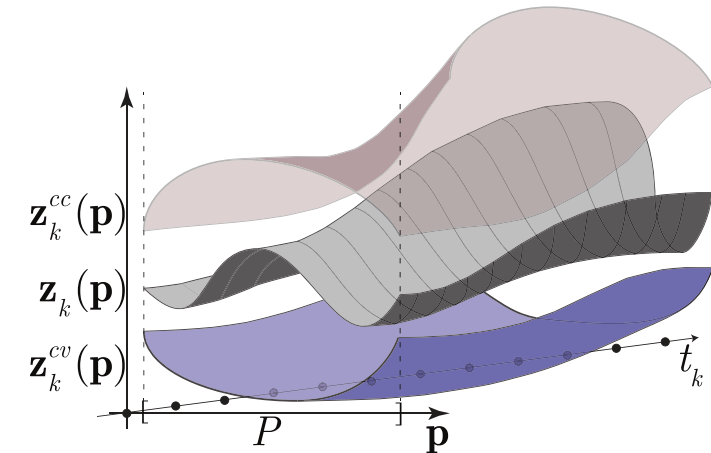
Implicit Functions⁷



Continuous Random Variables⁸



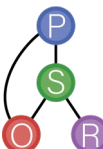
ODEs and DAEs⁹



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

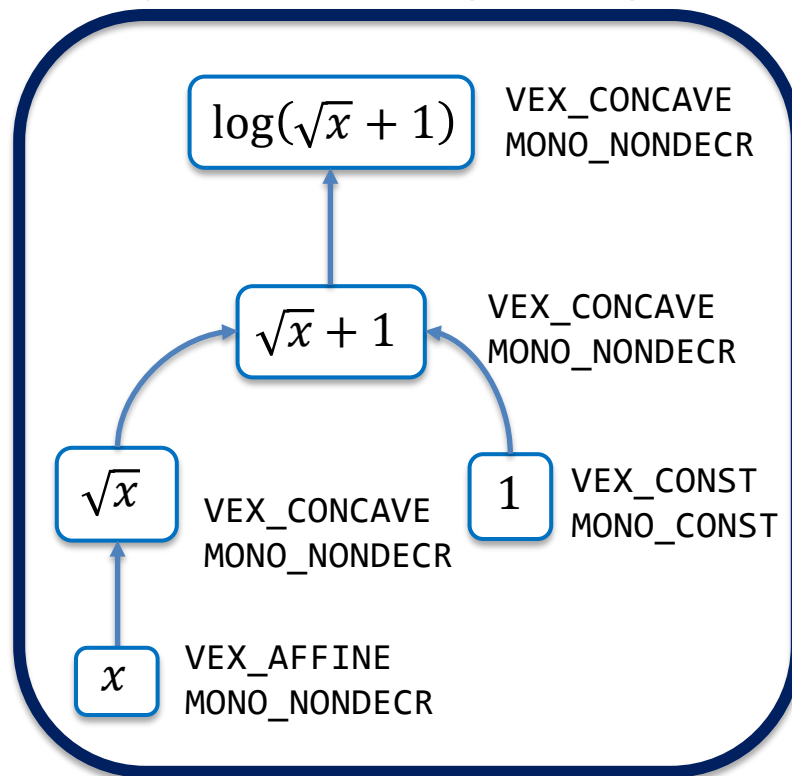
8. Shao, Y. and Scott J.K. **Convex relaxations for global optimization under uncertainty described by continuous random variables,** *AIChE Journal*, (2018): 3023 – 3033.

9. Wilhelm, M.E.; Le, A.V.; and Stuber, M.D. **Global Optimization of Stiff Dynamical Systems.** *AIChE Journal: Futures Issue*, 65 (12), (2019).

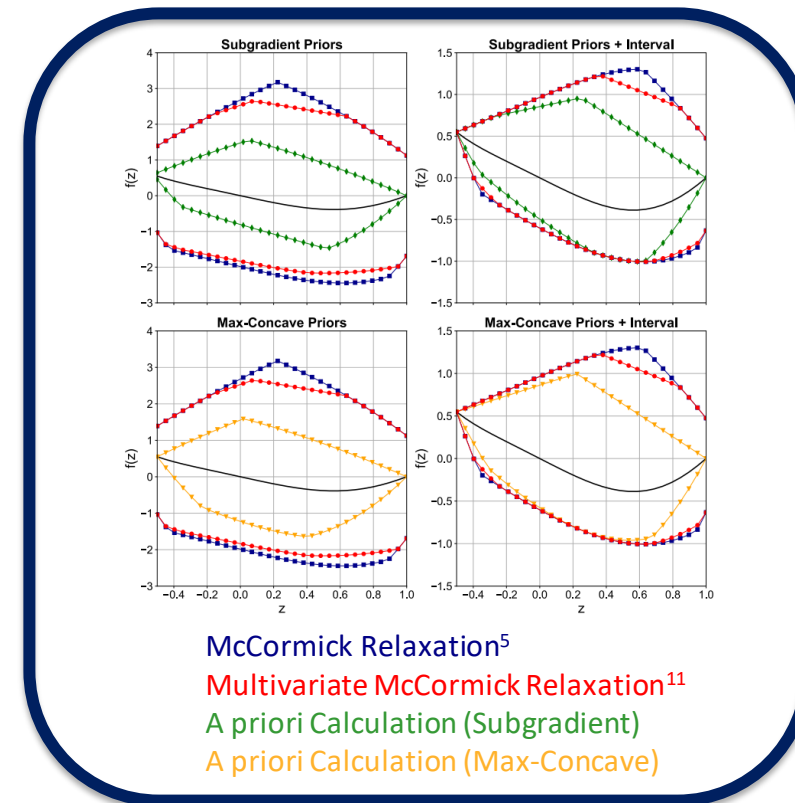


Additional Features

Built-in Convexity Detection (Disciplined Convex Programming¹⁰, etc.)



Improved Composite Bilinear Relaxations²



2. Wilhelm, M.E., & Stuber, M.D. **Improved Convex and Concave Relaxations of Composite Bilinear Forms.** *Journal of Optimization Theory and Applications*, **197** (2023): 174-204.

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

10. Grant, M., Boyd, S., & Ye, Y. (2006). **Disciplined convex programming.** In *Global optimization* (pp. 155-210). Springer, Boston, MA.

11. Tsoukalas, A., and Mitsos, A. **Multivariate McCormick relaxations.** *Journal of Global Optimization*, 59.2-3 (2014): 633-662.



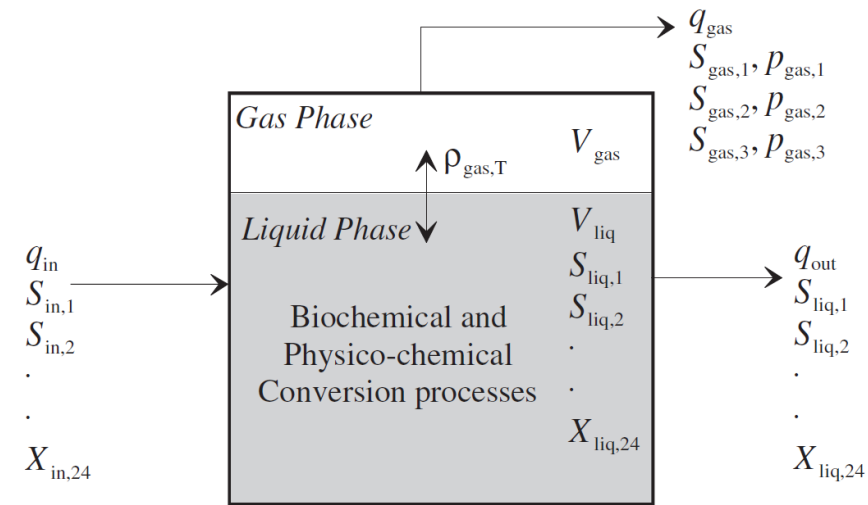
Addressing AnD Optimization

➤ Optimization of a **dynamical system**

➤ **Hybrid modeling** approach

- Complex mechanistic model
- Integrated machine learning elements

➤ **Higher dimensionality** than typical solvable global optimization problems



$$\frac{dS_{\text{gas},i}}{dt} = \frac{V_{\text{liq}} \rho_{i,T}}{V_{\text{gas}}} - \frac{q_{\text{gas}} S_{\text{gas},i}}{V_{\text{gas}}}$$

$$\frac{dS_{\text{liq},i}}{dt} = \frac{q_{\text{in}} S_{\text{in},i}}{V_{\text{liq}}} - \frac{q_{\text{out}} S_{\text{liq},i}}{V_{\text{liq}}} - \rho_{i,T} + \sum_{j=1-19} \rho_j \nu_{i,j}$$

$$\frac{dX_{\text{liq},i}}{dt} = \frac{q_{\text{in}} X_{\text{in},i}}{V_{\text{liq}}} - \frac{q_{\text{out}} X_{\text{liq},i}}{V_{\text{liq}}} + \sum_{j=1-19} \rho_j \nu_{i,j}$$



Addressing AnD Optimization

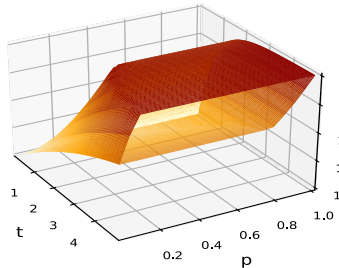
Global Dynamic Optimization



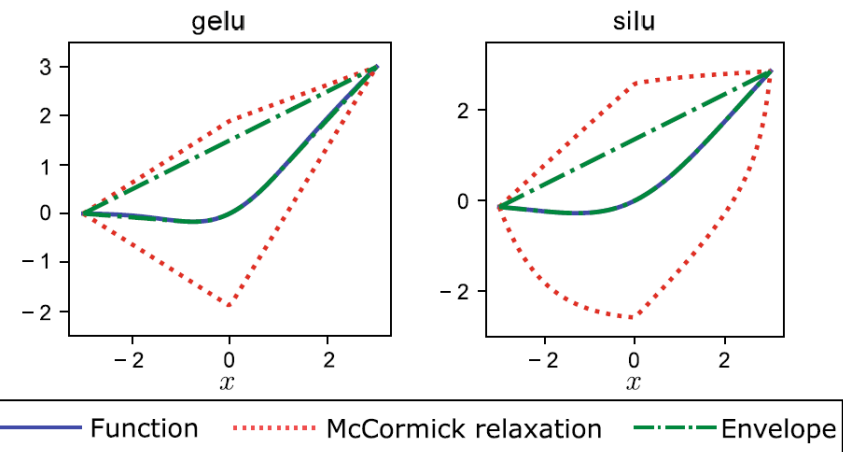
DynamicBounds.jl¹²

$$\frac{dx}{dt} = \exp(p) \sin(x)(2 - x),$$

$$x(0) = 1, \quad p \in [0.01, 1], \quad t \in [0, 5]$$



Activation Function Envelopes¹³



- Enables global optimization with embedded ANN surrogate models

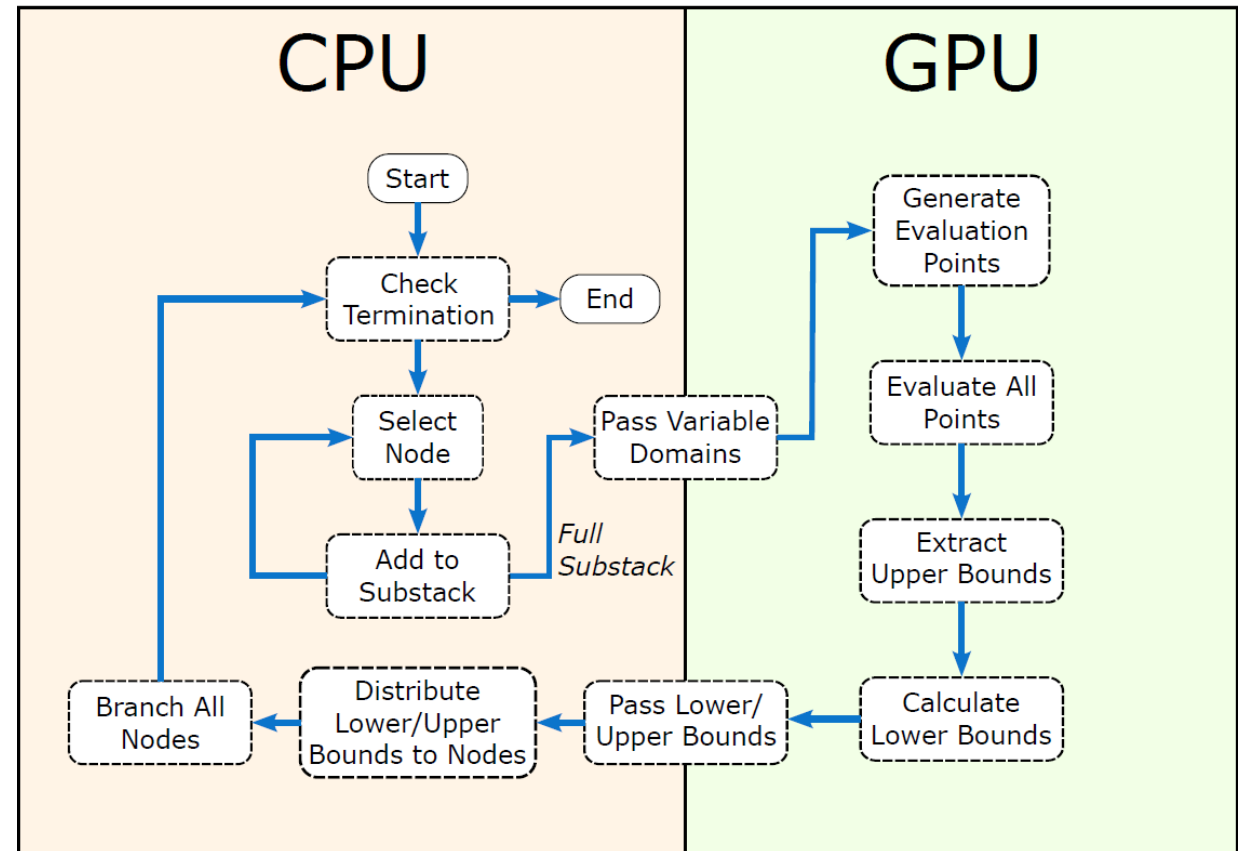
12. Wilhelm, M. E., **DynamicBounds.jl**, (2020), GitHub repository, <https://github.com/PSORLab/DynamicBounds.jl>

13. Wilhelm, M.E., Wang, C., Stuber, M.D. **Convex and concave envelopes of artificial neural network activation functions for deterministic global optimization.** *Journal of Global Optimization* (2022)

Parallelism

Working GPU-based algorithm

- **SourceCodeMcCormick.jl**¹⁴
- EAGO will soon incorporate **GPU acceleration** option
- Will also add **multi-core CPU** support at solver level rather than only subsolvers



14. Gottlieb, R.X. et al. Automatic source code generation for deterministic global optimization with parallel architectures. *Under Review*.

Other Notable Updates

EAGO v0.8

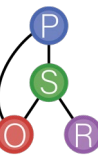
- **Fully compatible** with latest version of JuMP
 - Major changes to backend nonlinear expression handling
- Additional **use-case examples**
- **Improved formatting** for outputs, docstrings, and comments

On the horizon:

- Migrating features into “extensions”
 - More consistent user experience
- Documentation website overhaul



EAGO-notebooks



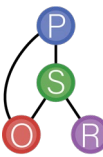
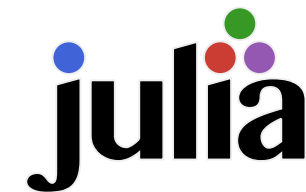
Conclusions

EAGO — An extensible deterministic global optimizer

- **High performance solver**
- **Open-source and free** for non-commercial use
- Designed for **user-defined functions** and routines

Future Outlook

- Parallel computing capability (GPU/CPU)
- Improvements to user-friendliness
- Updates to documentation



Acknowledgements

Members of the Process Systems and Operations Research Laboratory
at the University of Connecticut (<https://psor.uconn.edu/>)



UCONN
UNIVERSITY OF CONNECTICUT



Funding:

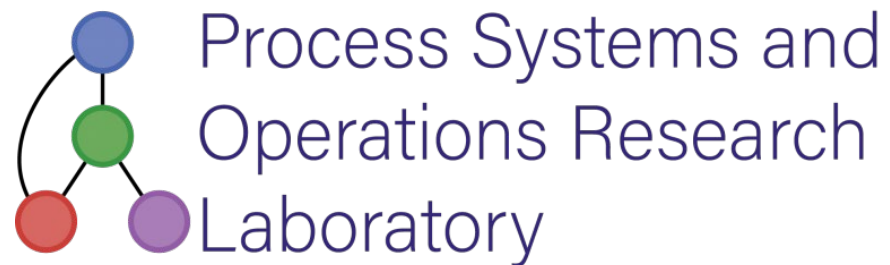
National Science Foundation, Award No.: **1932723**

DOE / EERE / AMO Award No.: **DE-EE0009497**

Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation, the Department of Energy, or the United States Government.



Questions?



<https://www.psor.uconn.edu>



<https://www.github.com/PSORLab/EAGO.jl>

