

Recent applications of machine learning and life cycle assessment to carbon capture

Gonzalo Guillén-Gosálbez, ETH Zurich

24th March 2025, Edinburgh

Current fossil-based chemical industry is unsustainable



Renewable C:

- **CO**₂ (CCU)
- **Biomass**
- **Chemical products waste**

To what extent can technologies contribute to sustainable chemicals production?



ETH zürich

How to quantify sustainability performance?

• Life cycle assessment of chemical systems: Electricity **Process simulation Chemical reaction** f = 35 °C P = 45 - 55 bar 2,000 kgmole/h T = 25 °C P = 1 bar Heat $CO_2 + 3H_2 \rightarrow CH_3OH + H_2O$ T = 50 °C P = 45 - 55 ba T = 63.75 °C P = 1.0 bar T = 35 °CP = 2 bar → Methano T = 63.75 °C P = 1.0 bar Reactants T = 35 °C P = 45 - 55 bar X kg CO₂ 4,500 - 6,500 kgmole/ T = 25 °C P = 1 bar $Y kg H_2$ T = 180 - 240 °C P = 45 - 55 bar T = 109.3 °C P = 1.4 bar T = 80 °CP = 2 bar INPUT VARIABLES **Direct emissions** Reaction temperature Reactor volume ec **Reaction pressure** Hydrogen flow R Reflux ratio Purge percentage Emissions per unit of flow Fossil MeOH: 0.72 kg CO₂eq/kg **Technology A** $f_1(x, y), \dots, f_k(x, y)$ min h(x,y) = 0s.t. Green MeOH: -0.68 kg CO₂eq/kg $g(x,y) \le 0$ **Technology B** Environment $x \in \Re^n, y \in \{0,1\}^m$ Cradle Grave Technology ...

Energy & Environmental Science **2019**, 12, 3425-3436 Chemical Engineering Science **2021**, 246, 116891





Challenges in sustainable engineering

- How to compare emerging technologies?
 - 3. Supply chain/life cycle
 - 2. Process flowsheets
 - 1. Experimental work

 $2 \rightarrow 3 \text{ Life cycle optimization}$ $1 \rightarrow 2 \text{ Generation of process flowsheets}$



• Key idea: Build analytical correlations from detailed simulations



- Hard to develop
- License/version issues

ETH zürich

F2

F3

Т

R

Can be directly used by experimental groups

Ρ

 $F_2 = f_1(F_1, P, T, R)$

F1

...

٠

٠

Easy to reproduce

• **Symbolic regression**^{1,2}: Mathematical expressions built using expression trees



Disjunction over each intermediate node $\{+\} \vee \{-\} \vee \{*\} \vee \{\div\} \vee ...$

F1

K1

Disjunction over each leaf node {F1} V {P} V {T} V {K1} V ...

F2 = F1*K1*(T/P)

÷

ETH zürich

2. MIT Press, Cambridge, MA **1992**





Challenges in sustainable engineering: Process simulation The Bayesian Machine Scientist¹

- Explores symbolic trees to provide **closed-form mathematical expressions**
- Markov chain Monte Carlo (MCMC) seeks the best expressions



- Mathematical expressions evaluated via the **description length**
 - $L(f_i) \approx \frac{BIC}{2} \log(p(f_i))$
 - $p(f_i)$: Probability of prior over expressions (corpus of ~5000 equations from Wikipedia)

The Bayesian Machine Scientist applied to carbon capture



Inputs: Pressure, temperature, input feed and CO₂ concentration

	Output	R ²	MRE
а	Min CU	0.9818	0.0103
b	Min HU	0.9921	0.0051
С	Net power	0.9986	0.0072
d	Amount of MEA	0.9922	0.0050

1004 kmol h⁻¹

38 °C

110 bar

99% mol. CO₂

Appl. Energy **2017**, 204, 353–361 ACS omega **2022**, 7 (45), 41147-41164

8





Symbolic regression in process optimization





Symbolic regression in process optimization: Methanol production



Symbolic regression in process optimization: Methanol production

Objective: Cost minimization

	Model	Training (s)	Optimization time (s)	OF – Surrogate (\$/kg)	OF – Aspen Plus [®] (\$/kg)	% Error
1	Aspen Plus®		8	-	1.55	-
2	BMS Hybrid	~14400	0.10	1.42	1.40	0.98%
3	BMS Black-box	~14400	14400*	1.53	1.66	-7.81%
4	Kriging Hybrid	30.2	14400*		No feasible sol	ution found
5	Kriging Black-box	1.3	14400*	1.34	1.41	-5.62%

Solved with GAMS 35.2.0 using BARON 21.1.13, sampling time ~2250 s on an Intel® Core i7-10700 CPU @ 2.90 GHz

BMS hybrid model:

- Best solution
- **Highest accuracy**: Minimum deviation from the rigorous simulation
- Other approaches unable to close the gap ("*" = 100% gap when maximum time is reached)



Challenges in sustainable engineering: Lack of LCA data

• Life cycle assessment: LCAs of more complex chemicals may face data gaps





ETH zürich

https://en.wikipedia.org/wiki/Vanillin

Challenge: Simple yet accurate methods to assess sustainability performance

Kirk-Othmer Encyclopedia of Chemical Technology 1997, 24, 812–825.

Challenges in sustainable engineering: Lack of LCA data





Challenges in sustainable engineering: Life cycle optimization

2030 Agenda for Sustainable Development



21 chemicals Renewable C & power, DAC, CCU and CCS

• **Superstructure** of technologies encompassing thousands of alternatives

 $\begin{array}{ll} \min_{x} & f(x) & \mbox{Objective function} \\ \mbox{s.t.} & h(x) = 0 & \mbox{Mass \& energy balances} \\ & g(x) \leq 0 & \mbox{Capacity constraints} \end{array}$





Challenges in sustainable engineering: Life cycle optimization 3 Good health and well-being 15 Life on land



- Fossil chemicals lead to large impacts on SDG 13
- Carbon neutral at minimum cost leads to burden-shifting
- Carbon neutral optimizing SDGs performance **reduces the potential collateral damage**

• **Hybrid production** patterns are required to produce chemicals sustainably



Challenges in sustainable engineering: Life cycle optimization



PULPO: An oracle to underpin sustainable technology development...





PULPO: An oracle to underpin sustainable technology development...



Generative Al (for identifying technological and sectoral

ETH zürich

improvement opportunities)

Conclusions



- Symbolic regression can simplify the process modelling task
- Machine learning algorithms can help cover data gaps in life cycle assessment
- Emerging technologies should be assessed following a multi-scale modelling approach
- Generative AI tools could be used to identify sustainable technological solutions

Take-home message

AI tools could help in guiding research efforts in carbon capture technologies and understanding their future role in sustainable industrial systems

