



Bioenergy recovery from sewage sludge in wastewater treatment plant : Machine learning and heterogeneous datasets

Anaerobic Digestion II, Room 1 Session XIII

16:30 pm – 16:45 pm , 16 June 2022

By Dr. Thomas T.H. TSUI
Research Fellow



Outline

- Background & Challenges
- Approach & Methodology
- Findings & Discussions
- Summary

Acknowledgement:

This research is supported by the National Research Foundation, Prime Minister's Office, Singapore under its Campus for Research Excellence and Technological Enterprise (CREATE) programme



Energy and Environmental Sustainability Solutions for Megacities (E2S2-CREATE)

E2S2-CREATE:

To understand and model for policy formulation and technology development, while reaching down from the city-wide model and developing deeper into the implementations at solving specific urban megacity challenges.



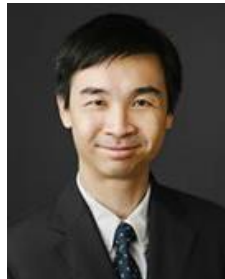
E2S2-CREATE Directors:

Prof. Yinghong PENG, Shanghai Jiao Tong University (SJTU)

Prof. Yen Wah TONG, National University of Singapore (NUS)



SJTU



NUS



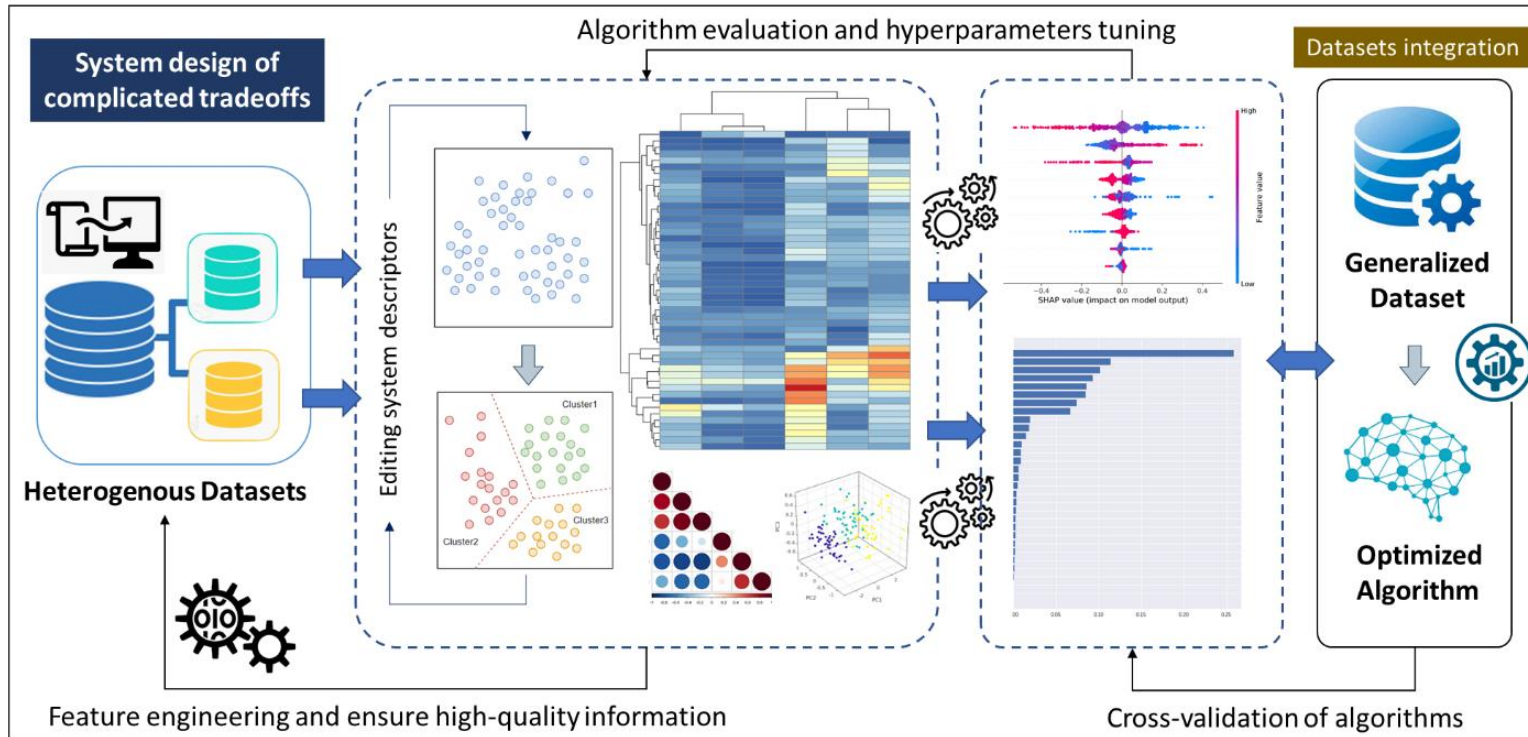
Background

- Urban waste management
 - High disposal costs and carbon emissions
 - Circular economy and a net-zero green future
- Urban Constraints and Challenges
 - Fast-changing needs and complexity
 - Space, economic factors, etc.
- Bioenergy recovery from recalcitrant biomass
 - E.g. Sewage sludge, Agricultural waste, Food waste (sometimes)
 - Complex structure and barriers to the penetration of hydrolytic enzymes
 - Pretreatment needs (e.g. thermal, chemical, electric methods)
 - Enhanced destruction; Reduced digestate volume; Compact digester

Challenges

- Technological constraints for system optimization
 - Slow experiments, labor intensive, and highly expensive
 - Tradeoffs with high-dimension of variables
 - Difficult to fully explore/ comprehend
- Conventional performance simulation
 - Time consuming; Unable to quickly handle increasing parameters
 - More confined to mechanistic derivation (e.g. ADM)
- A unified computational framework (to tackle prediction needs)
 - Artificial intelligence techniques in recent years; Fast-growing capacity
 - Multiple use of algorithms for compiling heterogenous datasets

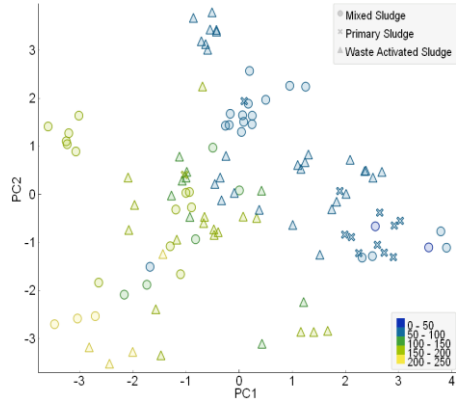
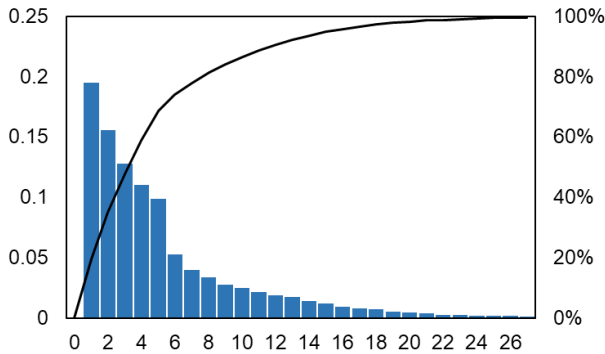
Approach & Methodology



The experimental data were collected from publications from 1990 to 2021, and there is a total of 236 experimental references selected for the architectural computation.

Findings & Discussions

- Main difficulties



AD_VS_removal	-0.07833	-0.02451	0.196619	-0.03683	-0.02229
Type_Secondary_Sludge	-0.07678	0.042612	0.006286	-0.01586	-0.02507
Pretreatment_Temperature	-0.06618	-0.22009	0.535018	-0.1591	-0.05858
I_TN_after	-0.05388	-0.02363	0.060836	-0.03356	-0.01898
Pretreatment_type=Ferrate + FNA	-0.03671	0.133421	-0.00303	0.015114	-0.09595
Chemical_Species=K2FeO4 +FNA	-0.03671	0.133421	-0.00303	0.015114	-0.09595
AD_Temperature	-0.03172	0.092333	0.026966	0.16173	0.09378
Chemical_Species=CaO2	-0.0303	0.001561	-0.02148	0.038327	-0.0098
Pretreatment_pH	-0.0252	-0.40318	0.274206	-0.34327	0.118492
Chemical_Species=K2FeO4+KOH	-0.02352	0.012167	0.03781	0.002821	0.015155
Pretreatment_Duration	-0.01673	0.004901	-0.40769	-0.00734	0.161547
Pretreatment_type=Alkali	-0.01247	-0.15805	0.073952	-0.16161	0.037584
I_SCOD_after	-0.00786	0.019144	0.075222	0.03747	0.174956
Pretreatment_type=Alkali, 2 stage Acidogenic	-0.00677	-0.00903	0.002891	-0.00352	0.005123
I_VS/TS_after	-0.00653	-0.00576	-0.02064	0.021541	-0.00639
I_VS_after	-0.00614	-0.00402	-0.01615	0.023149	-0.00648
Reactor_Type=Batch	-0.00279	0.009025	0.0046	0.025149	-0.00229
Chemical_Species=NaOH	-0.00178	-0.21256	0.100774	-0.13034	0.01337
Chemical_Species=KOH	-0.00071	-0.02488	0.007645	-0.01615	0.001909
Primary_Dosage	-0.00012	0.001054	0.001139	0.000813	0.000567
Chemical_Species=Na2SO3	0.000695	0.038985	-0.01482	-0.01121	0.049614
Pretreatment_type=Sulfite	0.000695	0.038985	-0.01482	-0.01121	0.049614
Pretreatment_type=Ferrate	0.000828	0.001411	0.000233	-0.00425	0.005431
Chemical_Species=K2FeO4	0.000828	0.001411	0.000233	-0.00425	0.005431
Reactor_Type=Semi Continuous	0.002792	-0.00903	-0.0046	-0.02515	0.002295
I_TS_after	0.008254	0.038941	0.124072	0.023693	-0.00585
Chemical_Species=Mixed Alkali	0.011337	0.003643	0.015427	-0.02338	-0.02543
TN_before	0.012384	-0.0312	0.02166	-0.00794	-0.04306
Chemical_Species=CaClO2	0.025476	0.030994	-0.0393	0.05091	0.046503
SCOD_before	0.028995	-0.2342	0.040404	0.098317	0.149508
AD_control_biomethane	0.0634	-0.42142	-0.45113	-0.07892	0.02577
Chemical_Species=Nitrous Acid	0.05442	-0.00674	-0.05923	0.165478	-0.00181
Pretreatment_type=Acid	0.05442	-0.00674	-0.05923	0.165478	-0.00181
AD_pretreatment_biomethane	0.057247	-0.38903	-0.38331	-0.20692	-0.08543
Type_Sludge_Mixture	0.076782	-0.04261	-0.00629	0.015857	0.025073
VS/TS_before	0.087726	-0.395	0.065531	0.082016	0.138826
TS_before	0.326067	-0.18971	0.147556	0.474796	-0.1028
VS_before	0.34002	-0.24285	0.112754	0.480298	-0.10467
AD_Pretreated_Duration	0.487633	0.127419	0.012606	-0.30699	0.088436
AD_Control_Duration	0.488059	0.124814	0.0122	-0.30783	0.086278
HRT/SRT	0.499658	0.165422	0.019729	-0.10075	-0.01299
components	PC1	PC2	PC3	PC4	PC5
variance	0.20843	0.195289	0.145843	0.111938	0.069103

- Final prediction performance

Scope	XGBoost			
	Prediction accuracy		Probabilities of advantaged prediction against others	
	R ²	kNN	SVM	NN
Thermal dataset	0.929	0.901	0.854	0.810
Chemical dataset	0.903	0.953	0.972	0.939
Generic algorithm	0.878	0.969	0.908	0.992

Summary

- A computational approach
 - to deal with prediction complexity & accuracy
 - to encounter dynamic changes in urban environments
- Experiment-derived simulation with proven accuracy
- A generic algorithm with transferable and growth potentials
- Next: Integration with other artificial intelligence techniques
 - E.g. Packaged programming for automated data analytics



Thank you!

