Neural Network-enabled Domain-consistent Robust Optimisation for Global CO_2 Reduction Potential of Gas Power Plants

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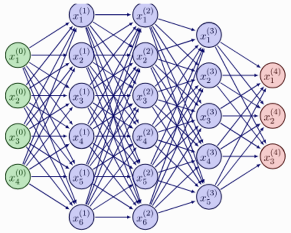
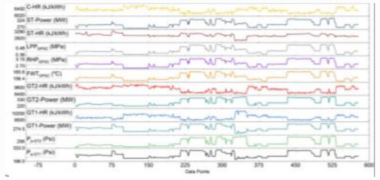
Problem Statement

- ✓ Energy sector is the largest contributor of CO_2 emissions [1]



- ✓ Neural networks are universal function approximators but black-box [2]

- ✓ Embedding artificial intelligence (AI) models into standard optimisation framework provides domain-inconsistent solutions, not implementable in industry [3]



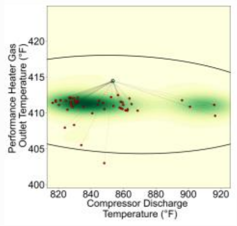
- ✓ Data-driven domain quantification and later its representation is difficult

[1] Edward Byers, and Steven J. Davis. "Energy systems in scenarios at net-zero CO_2 emissions." Nature communications 12, no. 1 (2021): 6096.
[2] Benítez, José Manuel, Juan Luis Castro, and Ignacio Requena. "Are artificial neural networks black boxes?." *IEEE Transactions on neural networks* 8, no. 5 (1997): 1156-1164
[3] Brynjolfsson, Erik, and A. N. D. R. E. W. Mcafee. "Artificial intelligence, for real." Harvard business review 1 (2017): 1-31.

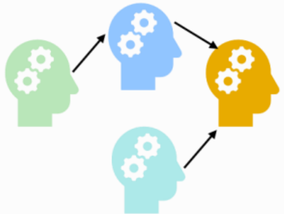
Objective

The objective of this research are as follows:

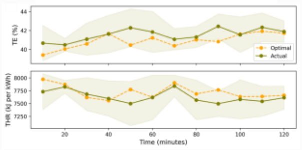
- ✓ Develop domain-constrained and data-driven robust optimisation framework with Mahalanobis trust regions



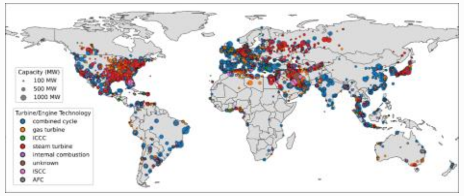
- ✓ Train multi-level surrogates for combined cycle gas power plant



- ✓ Verify the optimal solutions against the power plant data [4]



- ✓ Estimate annual CO_2 reduction potential from global gas power plants



[4] IEA (2025), Energy and AI, IEA, Paris https://www.iea.org/reports/energy-and-ai, Licence: CC BY 4.0

Method

- ✓ Feed-forward artificial neural network (ANN) models are trained with L_1 regularization and ADAM solver

- ✓ Two-stage robust optimisation framework is established:

$$\begin{gathered}\min_x f(x) = -f_{TE}(x) + f_{THR}(x) \\ (f_{Power}(x) - Power_{SetPoint})^2 < \varepsilon \\ (x-\mu)^T\, \Sigma^{-1}(x-\mu) < \tau^2 \\ f_{Power}(x) - \sum_{i=1}^{3} x_i < \Delta \\ x^L \le x \le x^U\end{gathered} \tag{1}$$

Here, thermal efficiency (TE) and turbine heat rate (THR) are the plant-level performance metrics which are optimised against $Power_{SetPoint}$

- ✓ The robustness of the optimal solution (x^*) is evaluated on variance ($V(x^*)$) produced in multi-objective function due to input perturbation (δ_k):

$$F(x^*) = \frac{\sum_{k=1}^{H} f(x^* + \delta_k),}{H} \quad V(x^*) = \frac{||F(x^*) - f(x^*)||}{||f(x^*)||} < \epsilon \tag{2}$$

Method

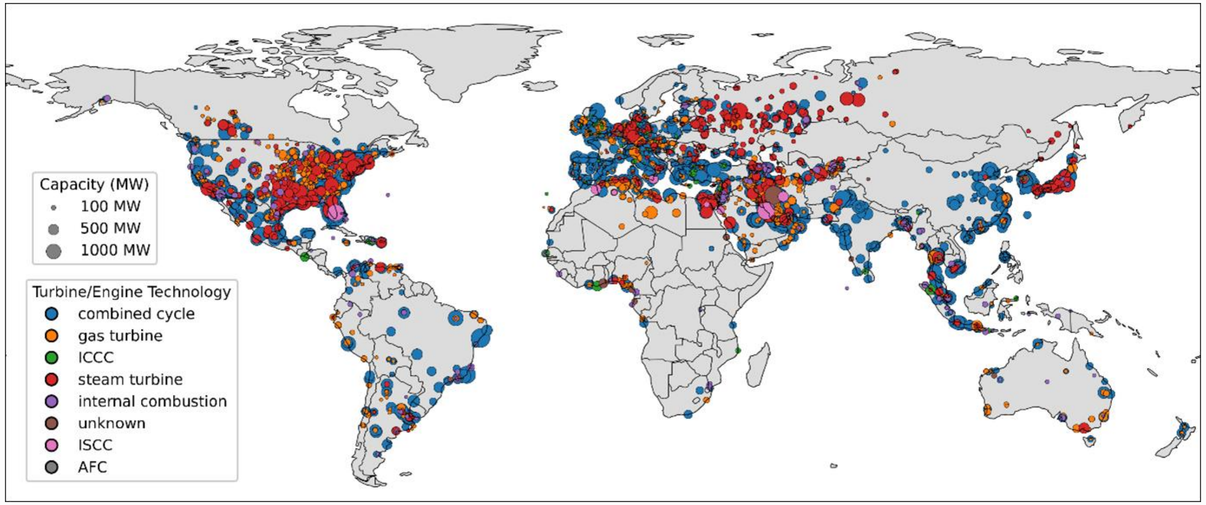
- ✓ The efficiency improvement (EI) in TE using historical operational data of combined cycle gas power plant (CCGPP) is estimated:

$$|Power_{actual} - Power_{SetPoint}| < \delta \qquad (3)$$

$$EI = \frac{1}{N}\sum_{k=1}^{N} median\ (f_{TE}(x^*) - (TE_{actual})_k \qquad (4)$$

- ✓ Annual CO_2 reduction potential from global fleet of gas power plants is calculated as:

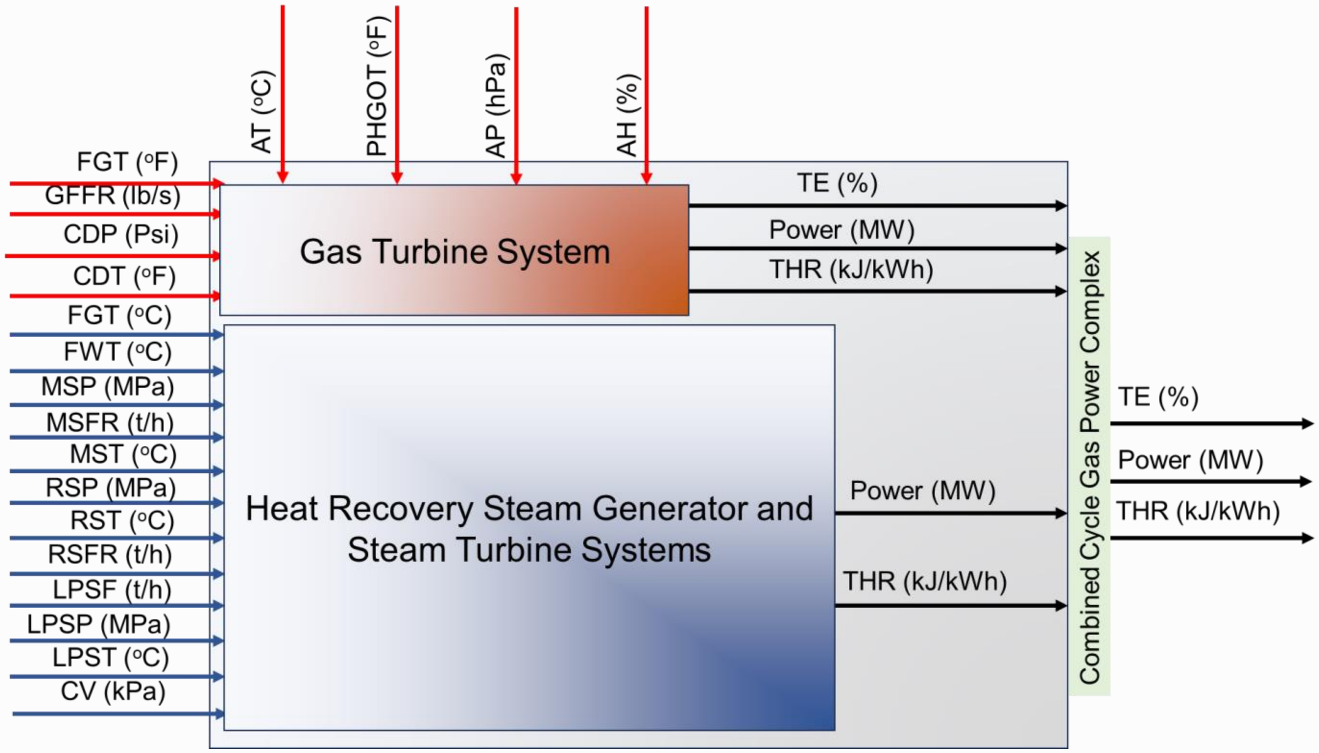
$$Annual\ CO_2\ Reduction = Capacity\ \times Capacity\ factor \times Hour \times Emission\ factor \times \left(1 - \frac{1}{1+EI}\right) \qquad (5)$$



Case Study: Combined Cycle Gas Power Plant

- ✓ TE, Power and THR are the performance variables

- ✓ Gas turbine-1 (GT-1), gas turbine-2 (GT-2), steam turbine (ST) are the sub-systems of combined cycle gas power plant (CCGPP)

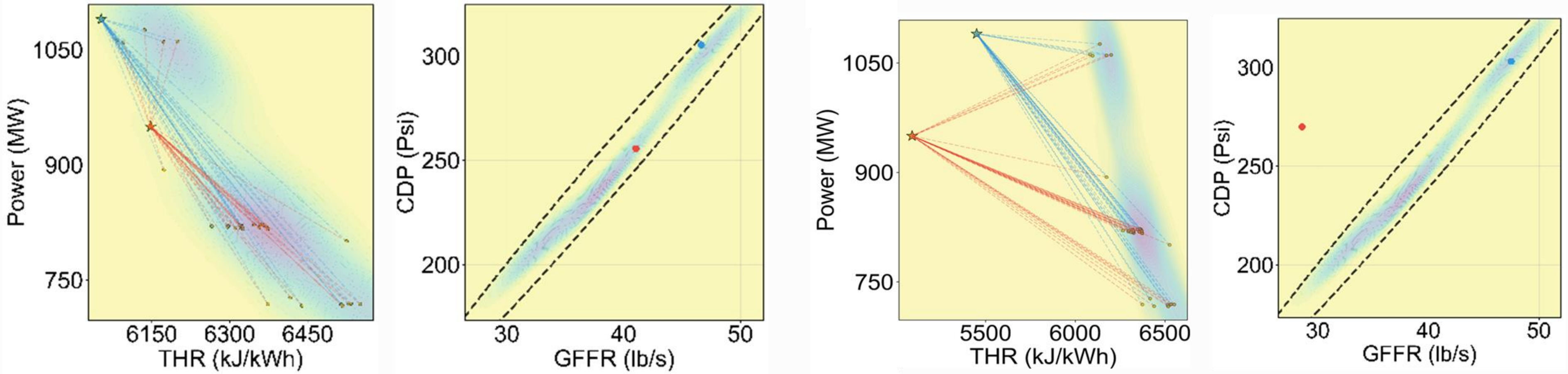


Case Study: Combined Cycle Gas Power Plant

✓ Three-layer ANN models are trained for performance variables of GT-1, GT-2, ST and CCGPP

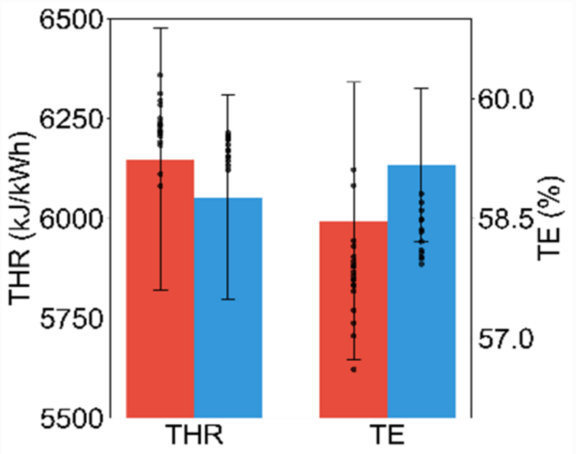
Performance Variables	Data	GT-1		GT-2		ST		CCGPP	
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
Power (MW)	Train	0.99	0.85	0.99	0.83	0.99	1.25	0.99	7.94
	Test	0.99	0.93	0.99	0.81	0.99	1.25	0.99	7.92
THR (kJ/kWh)	Train	0.88	203	0.89	163	0.95	23	0.89	49
	Test	0.84	221	0.86	181	0.95	24	0.85	55
TE (%)	Train	0.97	0.38	0.97	0.35	–	–	0.94	0.3
	Test	0.96	0.4	0.96	0.37	–	–	0.94	0.29

✓ The optimal solutions are compared, estimated *with* and *without* Mahalanobis constraint



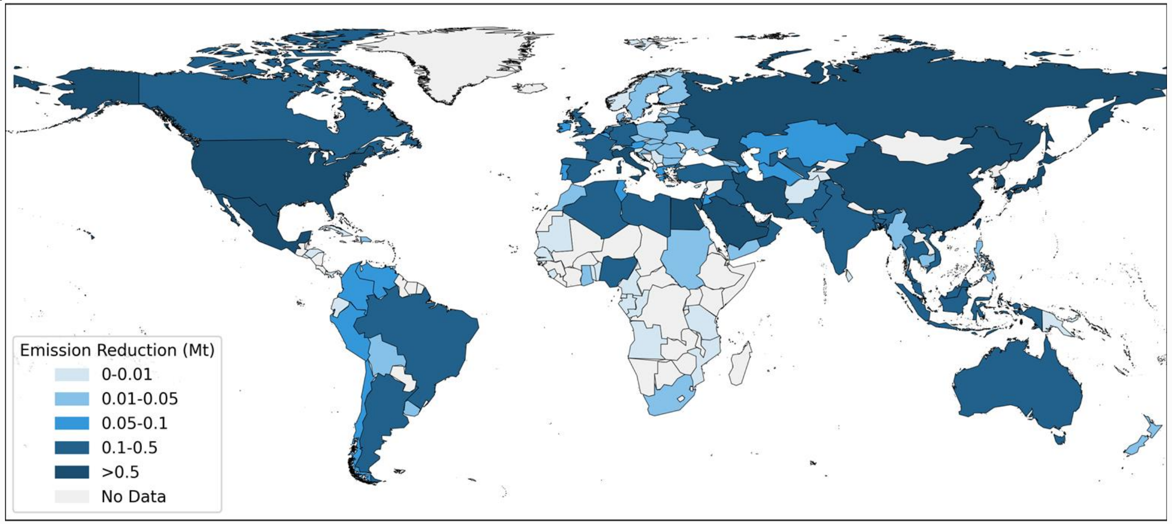
Case Study: Combined Cycle Gas Power Plant

- ✓ TE and THR are analysed at power generation of 950 MW and 1050 MW from CCGPP
- ✓ 0.76 percentage point (pp) EI is realised from plant-level operation optimisation of CCGPP



- ✓ 0.76 ± 0.5 pp EI is extended to global fleet of gas power plants [5]
- ✓ EI collectively avoids ~ 26 million tonnes (Mt) of annual CO_2 discharge

- **Asia:** 10.6 Mt
  China: 1.7 Mt
  Russia: 1.5 Mt
  Japan: 1.1 Mt
- **Americas:** 9.0 Mt
- **Europe:** 4.5 Mt
- **Africa:** 1.5 Mt



[5] Global Energy Monitor, "Global Oil and Gas Plant Tracker," 2025. [Online]. Available: https://globalenergymonitor.org/projects/global-oil-gas-plant-tracker/ Accessed: Aug. 12, 2025

Conclusions and Future Work

- ✓ Mahalanobis distance-based constraint embeds the data-driven domain up to human-defined tolerance level into optimisation problem
- ✓ Domain-constrained optimisation achieves **0.76% verified efficiency gain** with robustness under operational noise level (1%)
- ✓ Annual CO_2 reduction potential of **26.0 Mt** from global fleet of gas power plants
- ✓ AI-led real-time optimisation of gas power plants is a near-term, scalable decarbonization pathway

- ✓ Estimating the AI enabled emission reduction potential from chemical, and industrial sectors **in the future**

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Any Questions?
Happy to chat!