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 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

Objectives

- 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

Methods

- Feed-forward artificial neural network (ANN) models are trained with L_1 regularization and ADAM solver
- Two-stage robust optimisation framework is established:

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

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):

$$F(x^*) = \frac{\sum_{k=1}^{H} f(x^* + \delta_k)}{H} \tag{2}$$

$$V(x^*) = \frac{||F(x^*) - f(x^*)||}{||f(x^*)||} < \epsilon$$

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

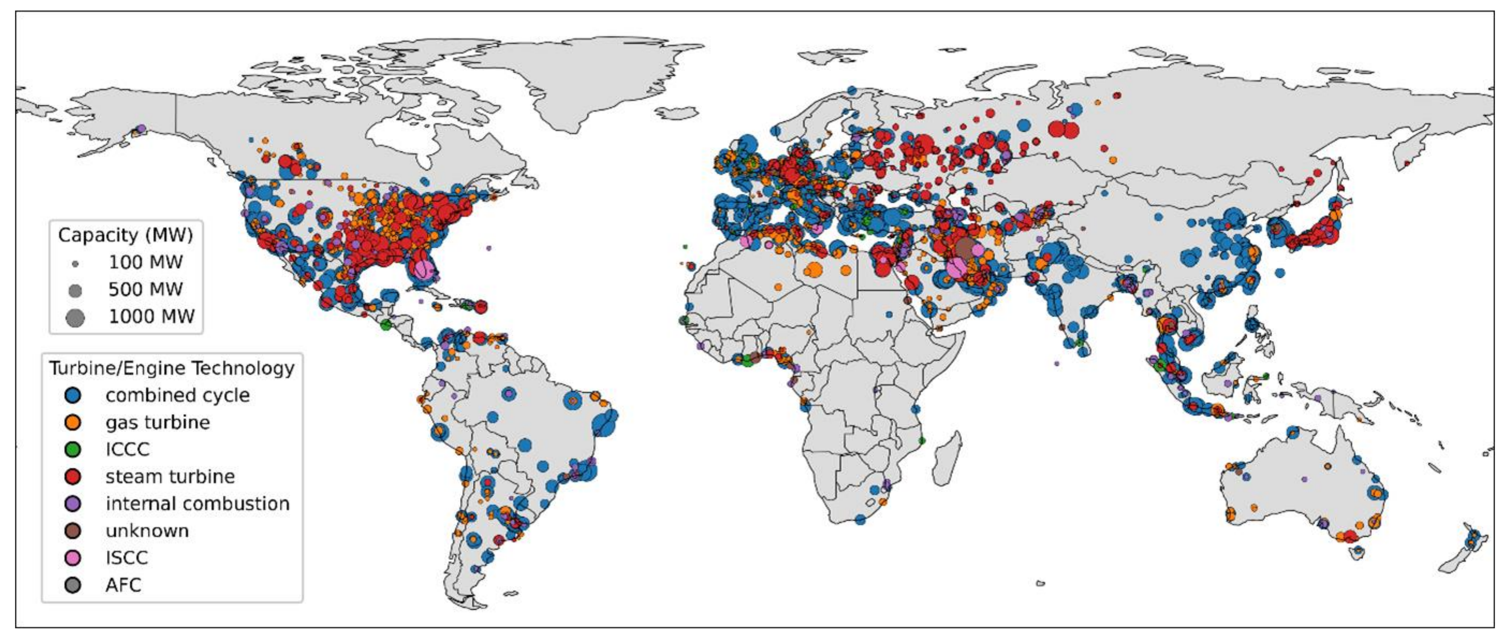
$$|Power_{actual} - Power_{SetPoint}| < \delta \tag{3}$$

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

Methods - Continued

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

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

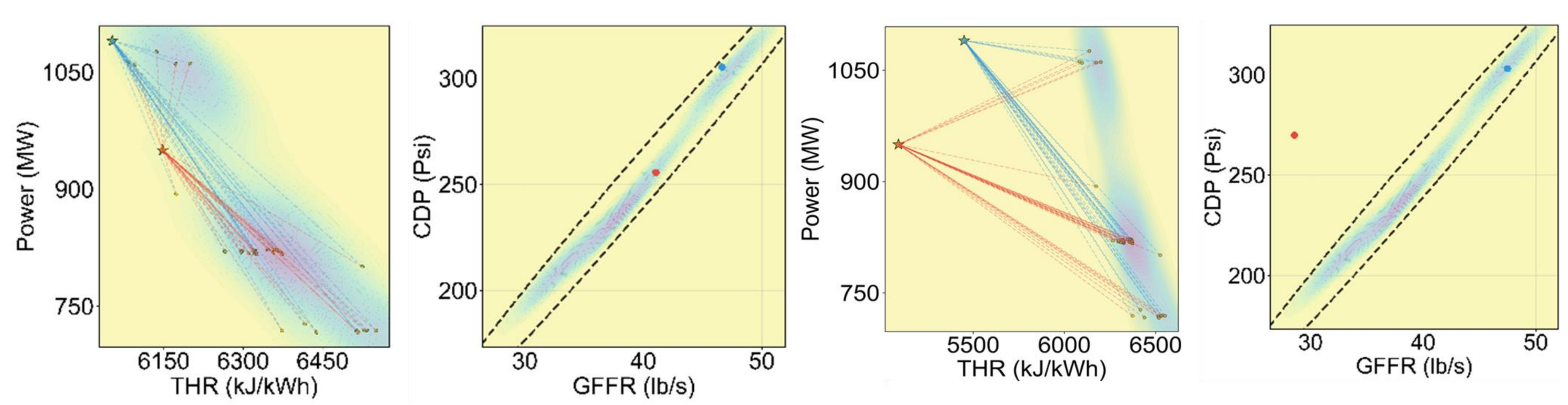


Results

- Three-layer ANN models are trained for performance variables of gas turbine-1 (GT-1), gas turbine-2 (GT-2), steam turbine (ST) and CCGPP

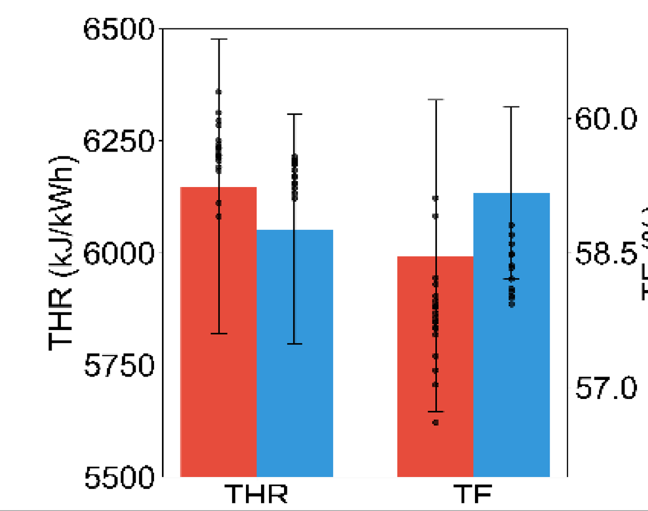
Performance Variables	Data	GT-1		GT-2		ST		CCGPP	
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
Power (MW)	Train	0.99	0.85	0.99	0.83	0.99	1.25	0.99	7.94
	Test	0.99	0.93	0.99	0.81	0.99	1.25	0.99	7.92
THR (kJ/kWh)	Train	0.88	203	0.89	163	0.95	23	0.89	49
	Test	0.84	221	0.86	181	0.95	24	0.85	55
TE (%)	Train	0.97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

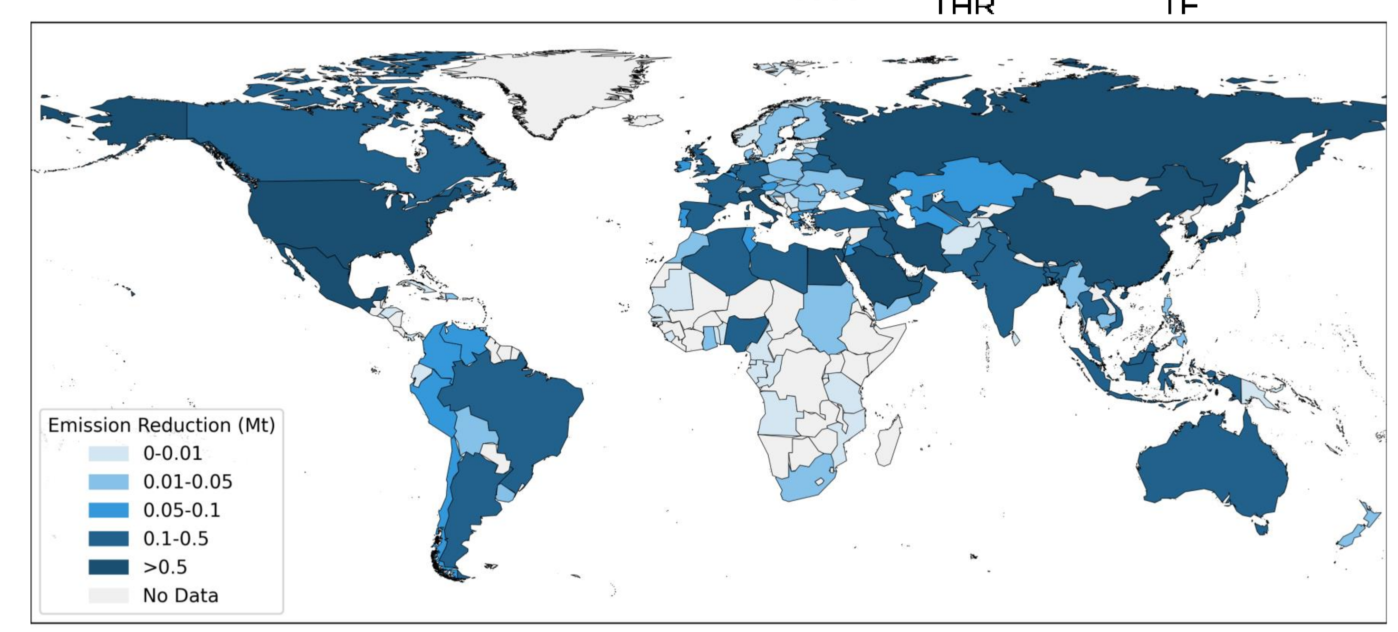
- TE and THR are analysed at power generation of 950 MW and 1050 MW from CCGPP
- The optimal solutions are compared, estimated *with* and *without* Mahalanobis constraint



Results - Continued

- 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 could avoid ~ 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





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, industrial and transportation sectors in the future

References

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