Accelerating domain-compliant AI adoption in industrial operations: A case of combined cycle gas power plant

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Problem Statement

- ✓ Neural networks are universal function approximators but black-box [1]
- ✓ Embedding AI models into standard optimisation framework provides domain-inconsistent solutions, not implementable in industry [2]
- ✓ Extrapolation beyond design conditions yields uncertain predictions, rendering models unfit for scaling performance [3]

Objectives

- ✓ Develop domain-constrained and data-driven robust optimisation framework with Mahalanobis trust regions
- ✓ Verify the optimal solutions against the power plant data [4]
- ✓ Domain-guided extrapolation of ANN beyond design conditions
- ✓ Development of open-source neural simulation platform

Method

Domain-consistent optimisation framework [5]:

- ✓ Domain-constrained robust optimisation problem is defined for multi-level operation of combined cycle gas power plant:

$$\begin{gathered}\min_x f(x) = -f_{TE}(x) + f_{THR}(x)\\ h(x) = 0\\ (f_{Power}(x) - Power_{SetPoint})^2 < \epsilon\\ (x-\mu)^T\,\Sigma^{-1}(x-\mu) < \tau^2\\ f_{Power}(x) - \sum_{i=1}^{3} x_i < \Delta\\ x^L \le x \le x^U\end{gathered} \qquad (1)$$

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 by variance ($V(x^*)$) produced in multi-objective function due to input perturbation (δ_k):

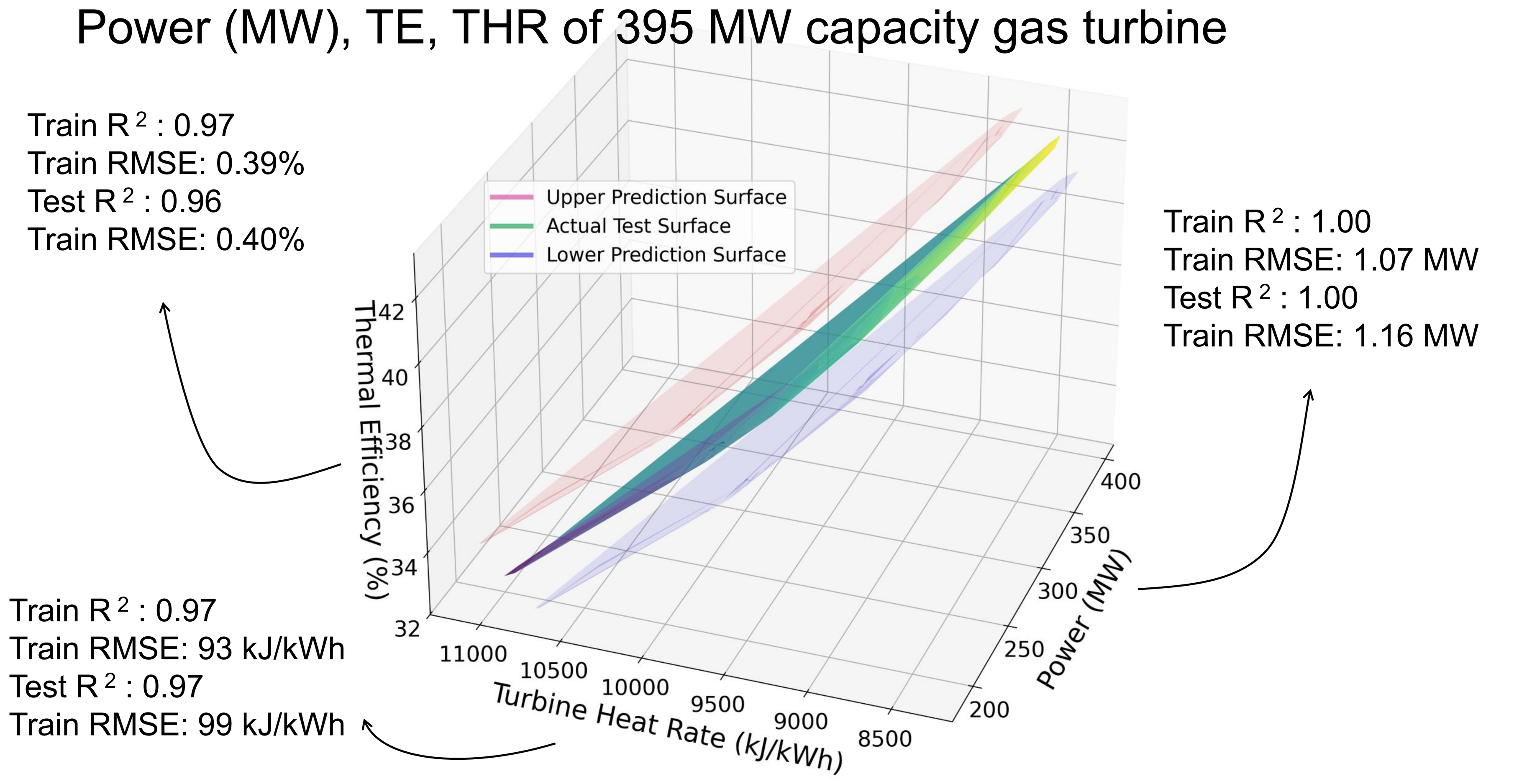
$$\begin{gathered}F(x^*) = \frac{\sum_{k=1}^{H} f(x^* + \delta_k)}{H}\\ V(x^*) = \frac{||F(x^*) - f(x^*)||}{||f(x^*)||} < \epsilon\end{gathered} \qquad (2)$$

Extrapolation of ANN model

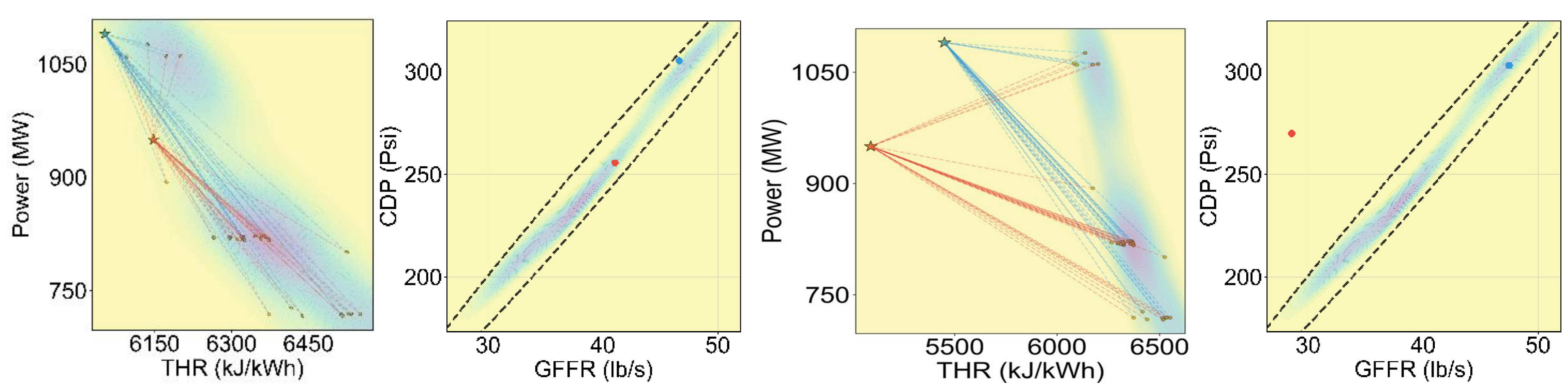
- ✓ ANN models are trained on **subsample** of dataset
- ✓ Extrapolation is carried out with optimisation problem (1)

Open-Source Neural Simulation Platform: A case of combined cycle gas power plant

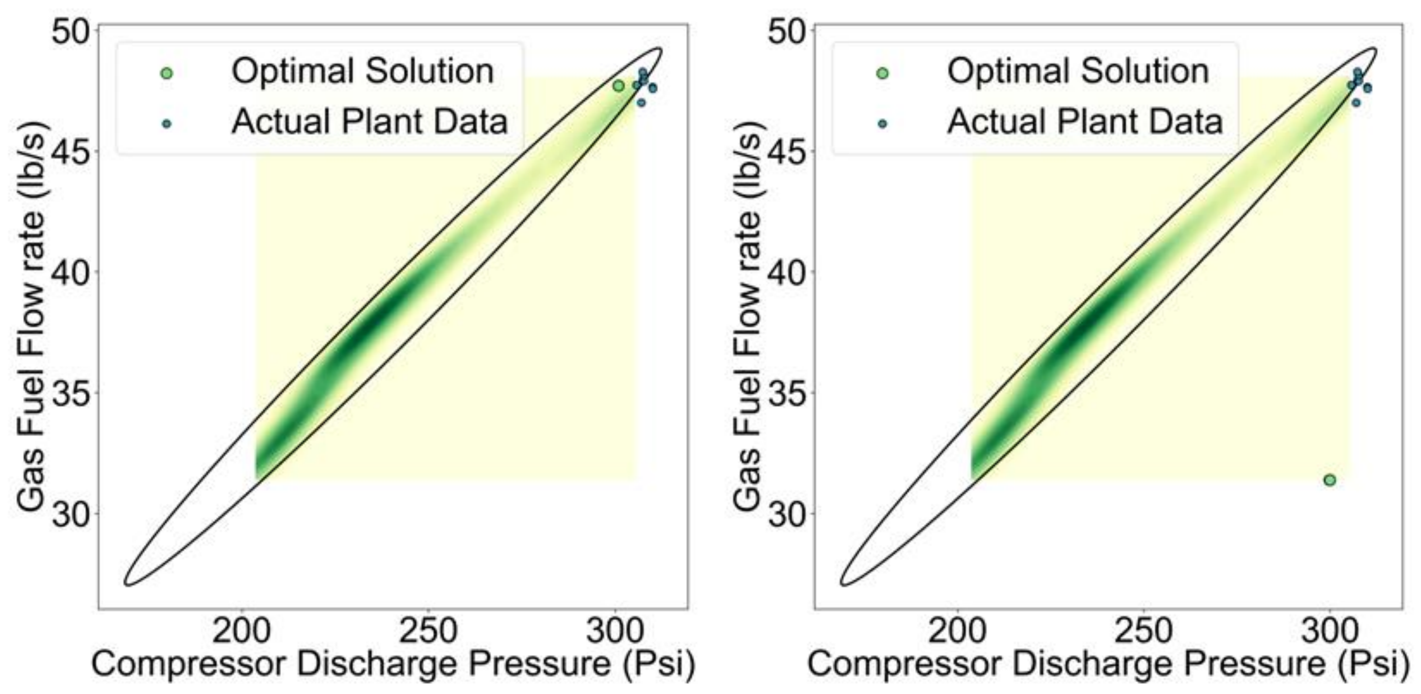
1. Three-layer ANN models are trained for performance variables, Power (MW), TE, THR of 395 MW capacity gas turbine



2. The optimal solutions are compared, estimated **with** and **without** Mahalanobis constraint for 1180 MW capacity gas power plant



3. ANN is trained on data ≤380 MW, with 381–395 MW retained as **ground truth** for extrapolated results



4. An open-source **explainable and uncertainty-aware simulation platform** for **real-time process optimisation** is developed

Neural Simulation Platform

$Power_{SetPoint}$	350	Input
Tolerance	80	

Power: 350 ± 2 MW
Thermal Efficiency: 42.10 ± 0.08 %
Heat Rate: 8465 ± 38 kJ/kWh
Output

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Conclusions & Future Work

- ✓ **Data-driven industrial domain knowledge** is quantified by Mahalanobis distance
- ✓ Solving the domain-constrained optimisation problems provides implementable solutions **for existing control layer** of industrial systems
- ✓ Domain-knowledge can help **safely extrapolate** ANN models for industrial applications
- ✓ Neural simulation platform adapts with **industrial constraints** and carries **real-time process optimisation**
- ✓ Future work on generalised framework **on model adaptation** with data drift and evolving process conditions

References

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