Beyond Research on Neural Networks: Data-Driven Robust Optimisation of Combined Cycle Gas Power Plant

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Problem Statement

- ✓ Neural networks are universal function approximators but black-box [1]
- ✓ Neural networks are point-predictors; do not provide prediction intervals
- ✓ How to carry out data-driven robust optimisation integrating the neural networks for multi-level operation of combined cycle gas power plant ?

Objectives

- ✓ Introduce data-information to infuse interpretability for neural networks
- ✓ Compute prediction intervals using neural network parameters space
- ✓ Present two-stage robust-optimisation framework embedding the neural networks

Data Information Integrated Neural Network (DINN)

- ✓ Feature association is computed by Pearson Correlation Coefficient (PCC)
- ✓ The loss function of DINN is customized to include PCC information for updating the parameters:

$$\mathcal{L} = \left(\frac{\lambda}{1+\lambda}\right).\frac{\sum(D-Z)^2}{N} + \left(\frac{1}{1+\lambda}\right).\frac{\sum_{i=1}^{m}(r_{X_i|D} - r_{X_i|Z})^2}{N} \quad (1)$$

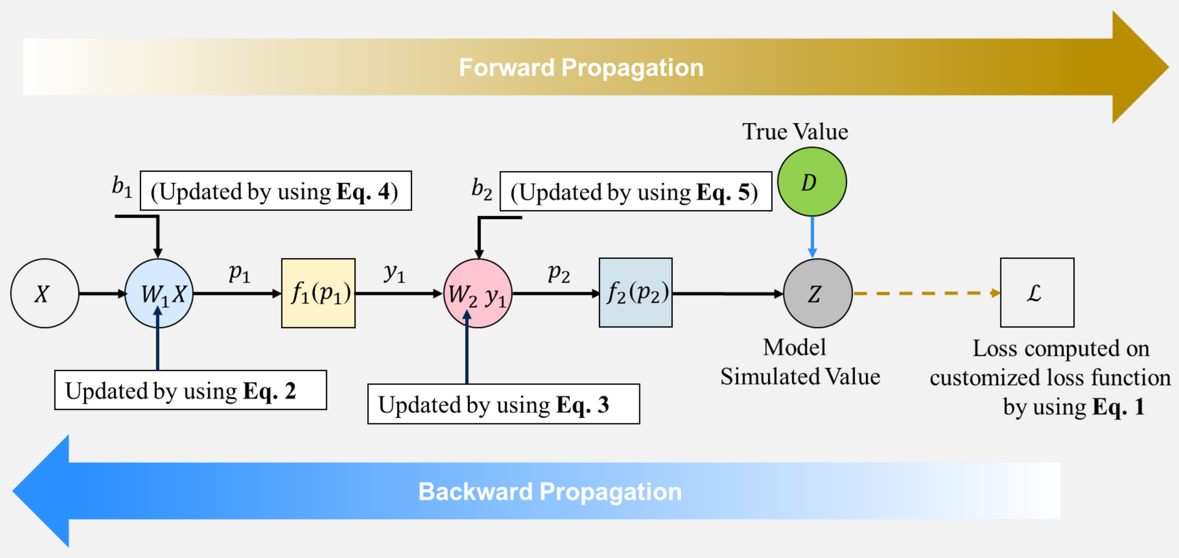
- ✓ Gradient descent with momentum algorithm updates the parameters:

$$W_1^{new} = W_1 + \eta\left(\beta V_{W_1} + (1-\beta)\left(\frac{2(D-Z)}{N} + r_{X_i|Z}.\left(\frac{X_i^{\mu}}{\mathcal{B}_i} - \frac{Z^{\mu}}{\mathcal{M}}\right)\right)W_2^T(1-y_1^2)X^T\right. \quad (2)$$

$$W_2^{new} = W_2 + \eta\left(\beta V_{W_2} + (1-\beta)\left(\frac{2(D-Z)}{N} + r_{X_i|Z}.\left(\frac{X_i^{\mu}}{\mathcal{B}_i} - \frac{Z^{\mu}}{\mathcal{M}}\right)\right)y_1\right. \quad (3)$$

$$b_1^{new} = b_1 + \eta\left(\beta V_{b_1} + (1-\beta)\left(\frac{2(D-Z)}{N} + r_{X_i|Z}.\left(\frac{X_i^{\mu}}{\mathcal{B}_i} - \frac{Z^{\mu}}{\mathcal{M}}\right)W_2^T(1-y_1^2)\right)\right. \quad (4)$$

$$b_2^{new} = b_2 + \eta\left(\beta V_{b_2} + (1-\beta)\left(\frac{2(D-Z)}{N} + r_{X_i|Z}.\left(\frac{X_i^{\mu}}{\mathcal{B}_i} - \frac{Z^{\mu}}{\mathcal{M}}\right)\right)\right. \quad (5)$$



Storage of Weights And Retrieval Method (SWARM)

- ✓ Online-mode of training is implemented for SWARM approach
- ✓ The loss function of neural network incorporates standard deviation term:

$$\mathcal{L} = \frac{(D-Z)^2}{2} + \frac{|D-Z|}{\sqrt{2}} \quad (6)$$

- ✓ Mean absolute difference based non-conformity score for D_1 at each epoch:

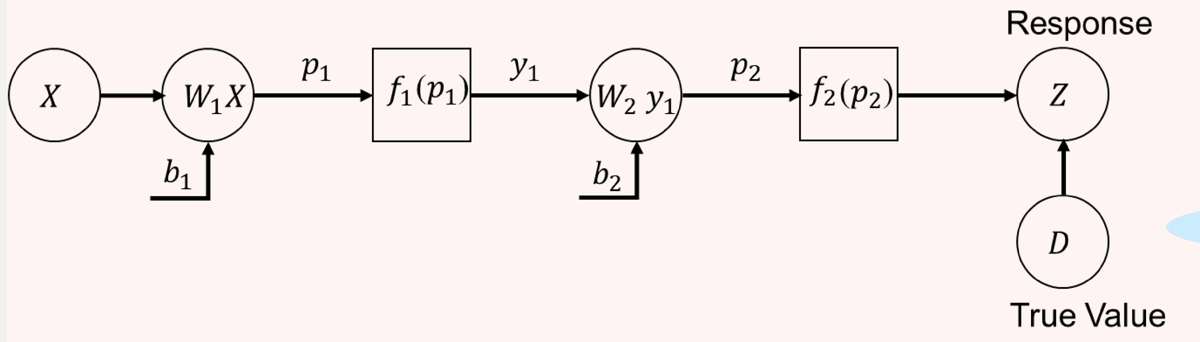
$$E_{1_{epoch}} = |D_1 - (Z_1)_{epoch}| \quad (7)$$

- ✓ SWARM based prediction interval (PI) on quantile value of $\hat{q}_{1-\alpha}$:

$$PI(Z_1)_{SWARM} = [Z_1 - \hat{q}_{1-\alpha}(E_{1_{epoch}}), Z_1 + \hat{q}_{1-\alpha}(E_{1_{epoch}})] \quad (8)$$

- ✓ The inductive conformal prediction (ICP) technique-based PI for test dataset on quantile value of $\hat{q}_{1-\alpha}$:

$$PI(Z_{test})_{ICP} = [Z_{test} - \hat{q}_{1-\alpha}(E_{cal}), Z_{test} + \hat{q}_{1-\alpha}(E_{cal})] \quad (9)$$



Data-Driven Robust Optimisation

- ✓ The multi-objective optimisation function is defined:

$$\min_x f(x) = (f_1(x) + f_2(x) + \cdots + f_n(x)) \quad (10)$$

subject to:

$$h(x) = 0$$
$$x^L \leq x \leq x^U \quad (11)$$

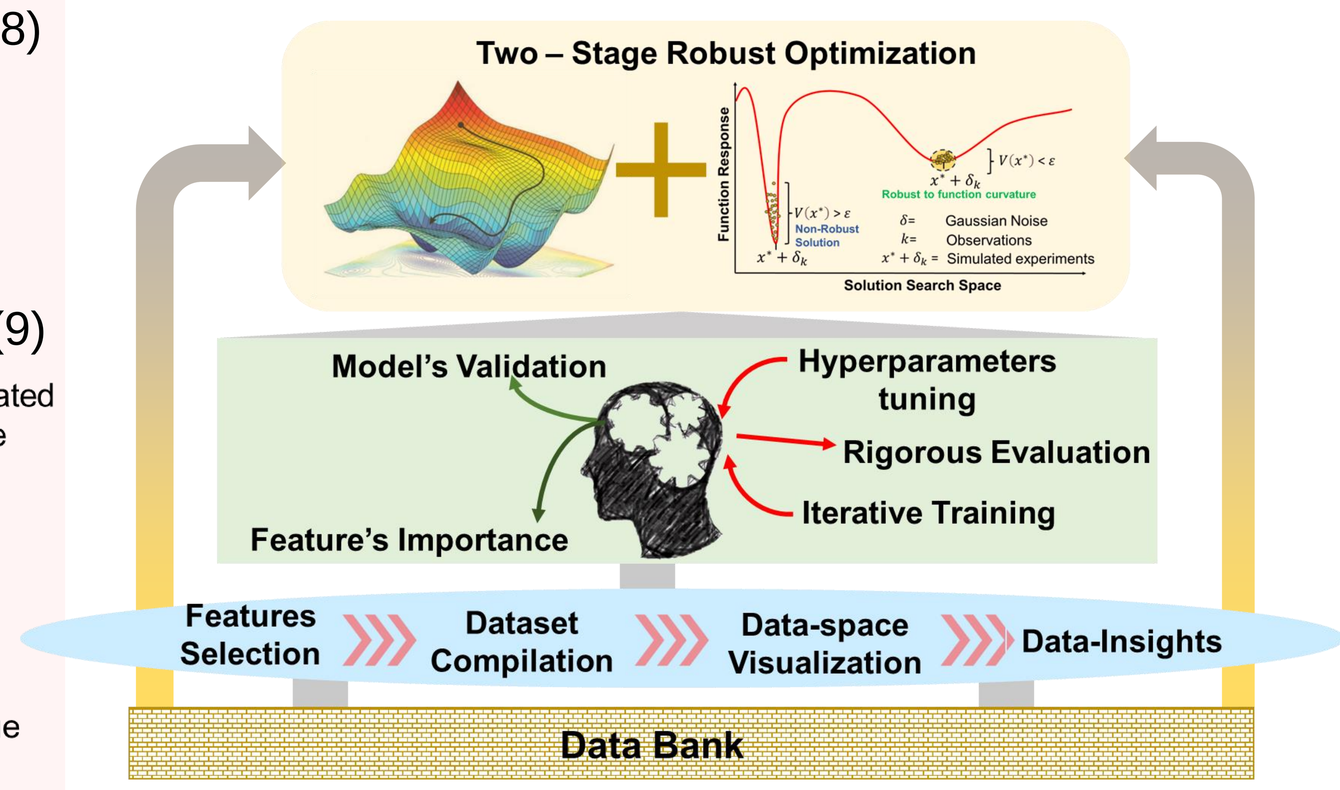
- ✓ The mean and variance in $f(x^*)$ for Monte Carlo simulations are computed as:

$$F(x^*) = \frac{\sum_{k=1}^{H} f(x^* + \delta_k)}{H} \quad (12)$$

$$V(x^*) = \frac{\|F(x^*) - f(x^*)\|}{\|f(x^*)\|} < \varepsilon \quad (13)$$

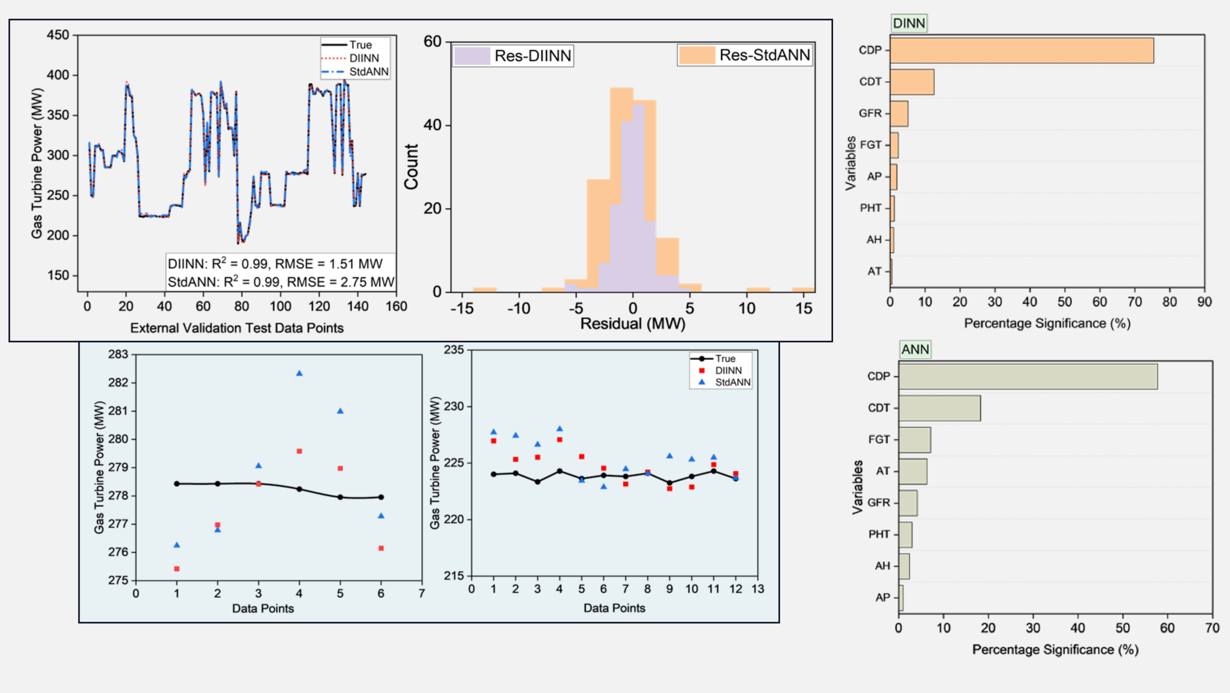
- ✓ The solution is "non-robust" when:

$$V(x^*) > \varepsilon \quad (14)$$

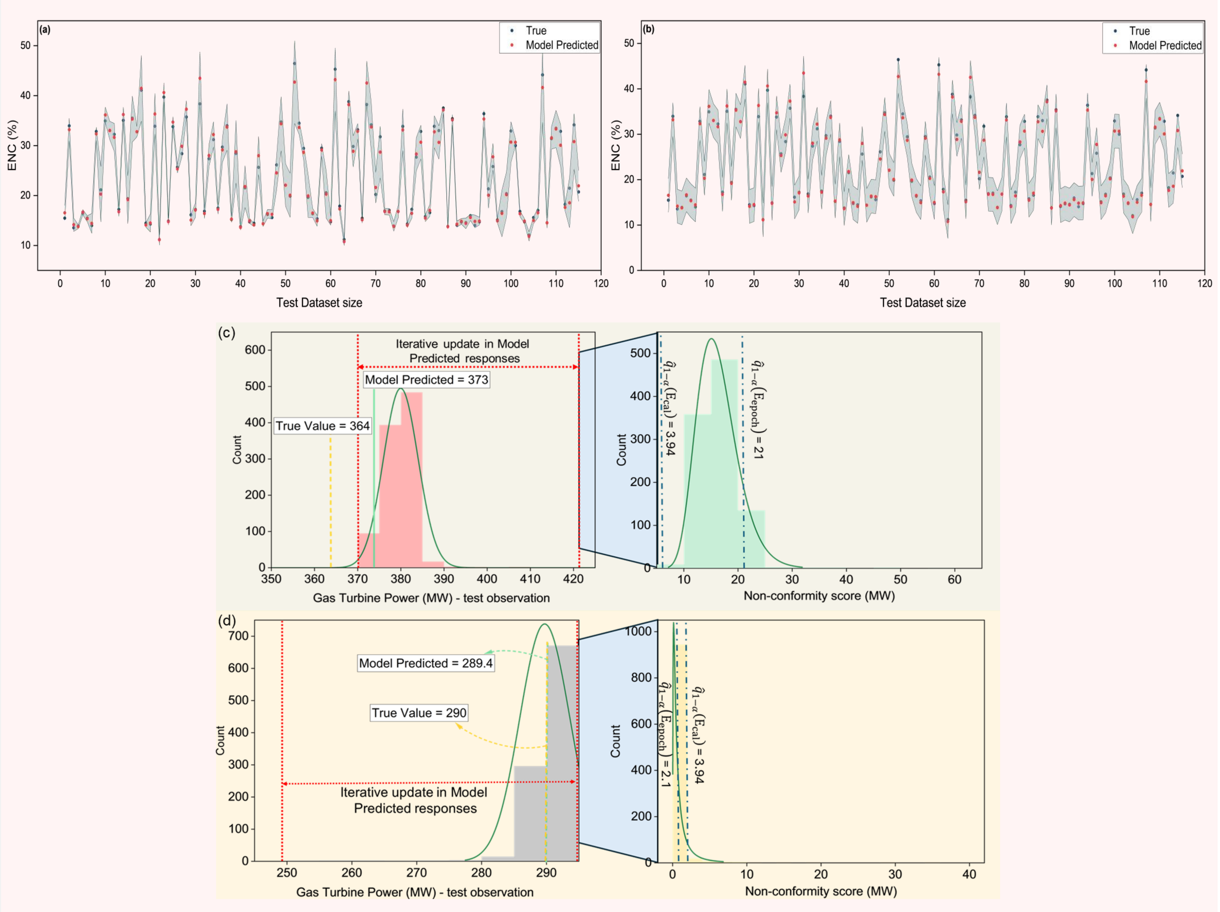


Case Studies

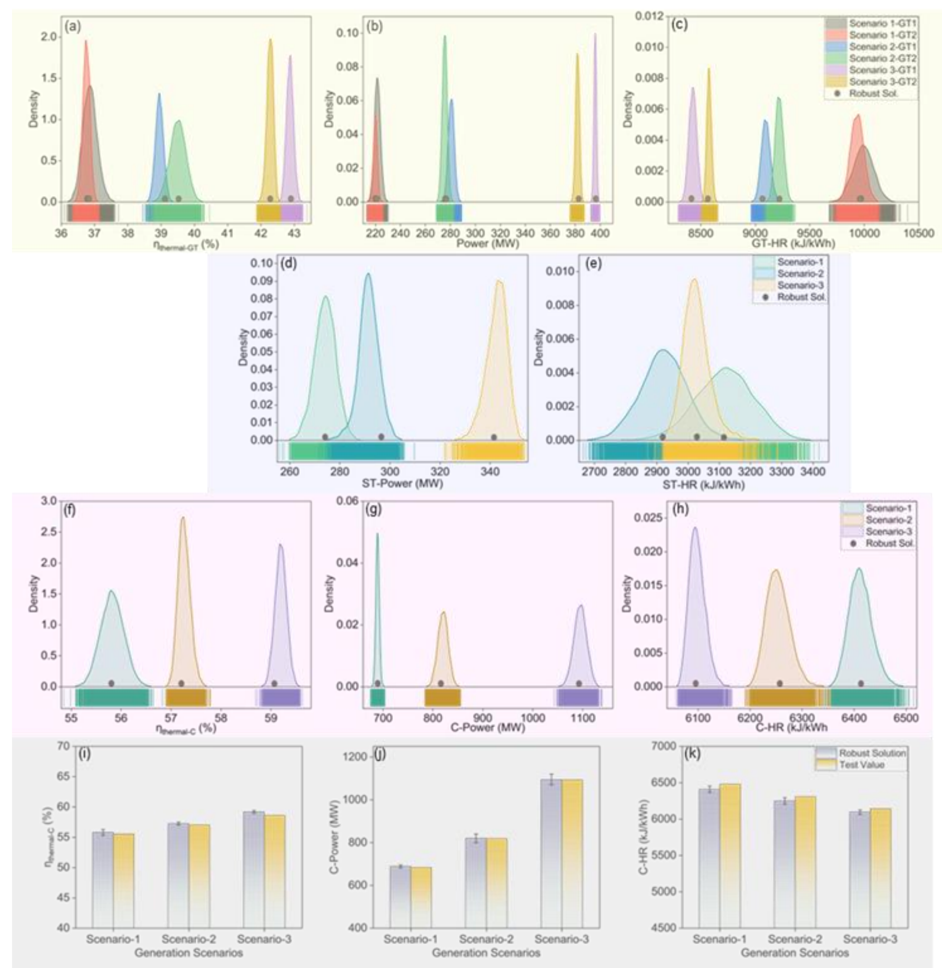
- ✓ DINN and ANN are trained to predict power generation from 395 MW capacity gas turbine system
- ✓ The feature importance for the power generation is established for well-trained DINN and ANN models [2]



- ✓ The PI are constructed by SWARM and ICP techniques
- ✓ Energy efficiency cooling data is used [3]



- ✓ Data-driven robust optimisation of 1180 MW capacity combined cycle gas power plant is carried out under top-down approach [4]



Conclusions & Future Work

- ✓ Expressions for the tuning of the model parameters are derived
- ✓ DINN based feature importance order better complies with domain knowledge than those of ANN
- ✓ SWARM based prediction intervals are better local–compliant than the fixed–width prediction intervals of ICP
- ✓ Top-down robust optimisation of combined cycle gas power plant reduces 62 ± 20 kt of CO_2 annually
- ✓ The future work will focus on bi-level optimisation of combined cycle gas power plant with neural networks

References

[1] 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

[2] Ashraf, Waqar Muhammad, and Vivek Dua. "Data Information integrated Neural Network (DINN) algorithm for modelling and interpretation performance analysis for energy systems." Energy and AI 16 (2024): 100363

[3] Ashraf, Waqar Muhammad, and Vivek Dua. "Storage of weights and retrieval method (SWARM) approach for neural networks hybridized with conformal prediction to construct the prediction intervals for energy system applications." *International Journal of Data Science and Analytics* (2024): 1-15.

[4] Ashraf, Waqar Muhammad, and Vivek Dua. "Driving towards net-zero from the energy sector: Leveraging machine intelligence for robust optimization of coal and combined cycle gas power stations." *Energy Conversion and Management* 314 (2024): 118645.

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Funding Source