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Seminar 37 – Reduced Order Modeling for HVAC&R Systems and their Components

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Application of Data-Driven Models for Positive Displacement Compressor Mapping

CHPB CENTER FOR HIGH PERFORMANCE BUILDINGS AT PURDUE

Learning Objectives

- **Understand the differences of data-driven models for positive displacement compressors.**
- **Explain how the minimum training dataset affects the accuracy of the models.**
- **Describe how uncertainties can be modeled and predicted.**
- Show legacy model performance in extrapolation and modulation scenarios
- How to convert a compressor map from a baseline refrigerant to a new refrigerant with lower GWP.
- Understand technical challenges associated with implementing nonlinear model order reduction approaches to Vapor Compression Cycle (VCC) applications.

Acknowledgements

The author would like to thank the Center for High Performance Buildings for the financial support

Outline/Agenda

- Introduction
- Objectives
- Model Structures
- Case Study
    1. ANN Model Structure
    2. Uncertainty and Extrapolation Studies
- Uncertainty Analysis
- Extrapolation Analysis
- Conclusions

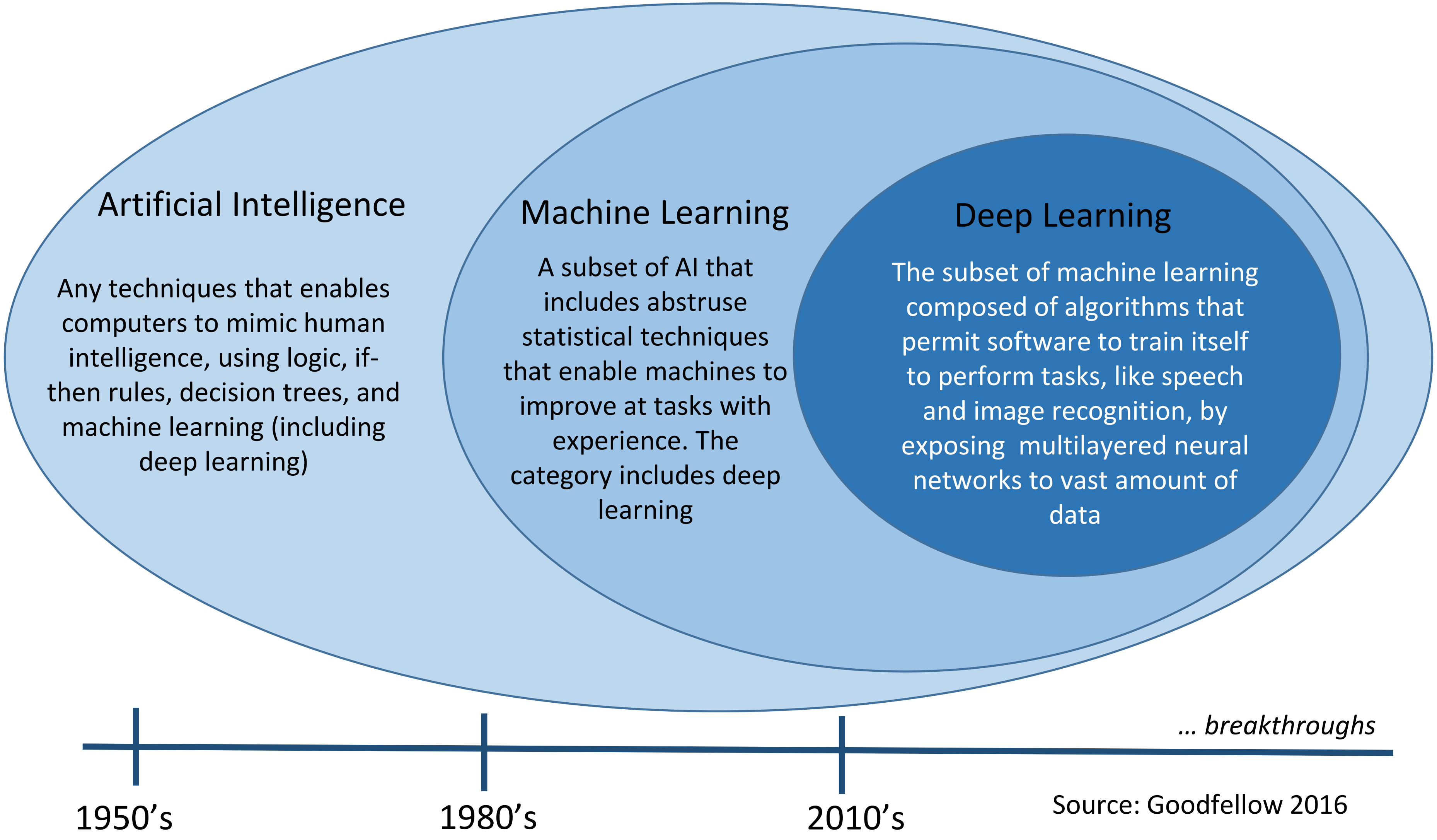
Introduction

- Performance mapping of positive displacement compressors is essential to simulate systems and their operations (e.g., control strategies)
  - Empirical (e.g., AHRI 540) and semi-empirical models have been proposed
- **Data-driven modeling** approaches are of interest because of their capabilities of handling complex non-linear systems:
  - **Pro:** no modeling assumptions; computationally efficient
  - **Cons:**
    - Usually, relatively large data-set required for training
    - Limited extrapolability
    - Unclear stability of the model when coupled with a system model
- The behavior of data-driven modeling approaches with limited data sets is still not completely investigated especially for this application

Introduction (cont'd)

- In recent years, data-driven modeling applied to refrigeration, air conditioning and heat pump systems (systems, components, thermophysical properties, etc.) has gained attention
- Examples of different data-driven models (non-exhaustive list):
  - Artificial Neural Networks (ANN)
  - Support Vector Machines (SVMs)
  - Classification and Regression Tree (CART)
  - Multiple Regression (MR)
  - Generalized Linear Regression (GLR)
  - Chi-squared Automatic Interaction Detector (CHAID)
  - Adaptive Neuro-Fuzzy Inference System (ANFIS)
- A few studies can be found on machine learning applied to positive displacement machines (Ledesma et al. 2015, Zendehboudi et al. 2017, Ma et al. 2020)

Introduction (cont'd)



Source: Goodfellow 2016

Objectives

Objectives:

- Generalized compressor mapping for conventional and novel compressors
- Need for accurate performance mapping while minimizing the number of test points
- Extrapolation capabilities
- Uncertainty of the predictions

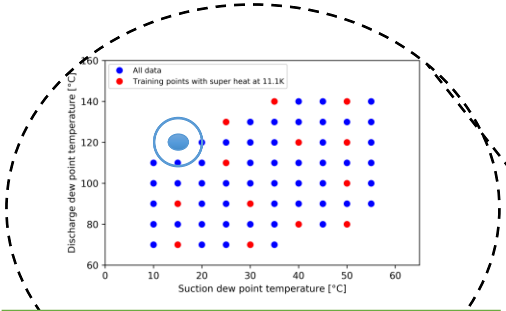
Methodology:

- Identify a compressor envelope and select minimum data points to capture the compressor operating envelope.
- Utilize a subset of data to train **ANN model**, and run the trained ANN model to predict the performance of the compressor.
- **Increase the number of training points and complexity of the model** in steps to quantify the improvements on the performance predictions.
- Utilize Gaussian Process regression to predict uncertainties

Objectives (cont'd)

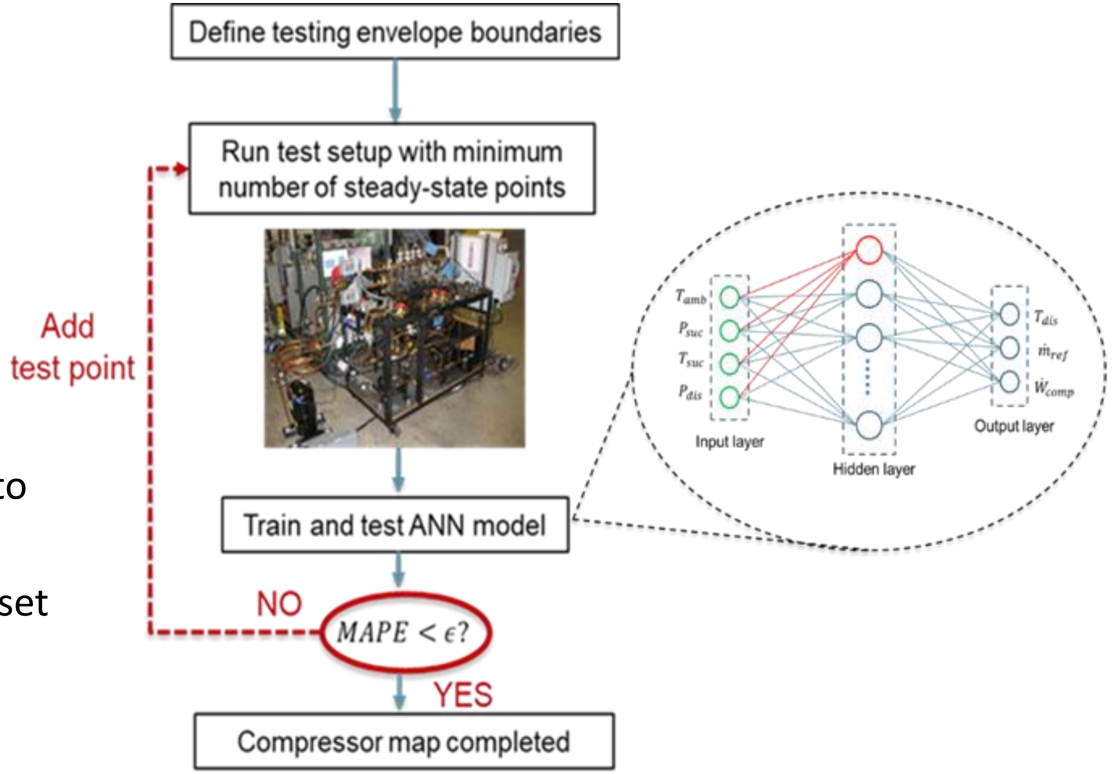
Methodology:

- ✓ Identify a compressor envelope and select minimum data points to capture the compressor operating envelope.
- ✓ **Increase the number of training points and complexity of the model** in steps to quantify the improvements on the performance predictions and **quantify the uncertainties**



$$P(\, f(\cdot) \mid \mathcal{D} \,) = P(\mathcal{D} \mid f(\cdot)) \times P(f(\cdot))$$

- Identify the point that contributes to the largest uncertainties
- Added into the training points dataset



Model Structures

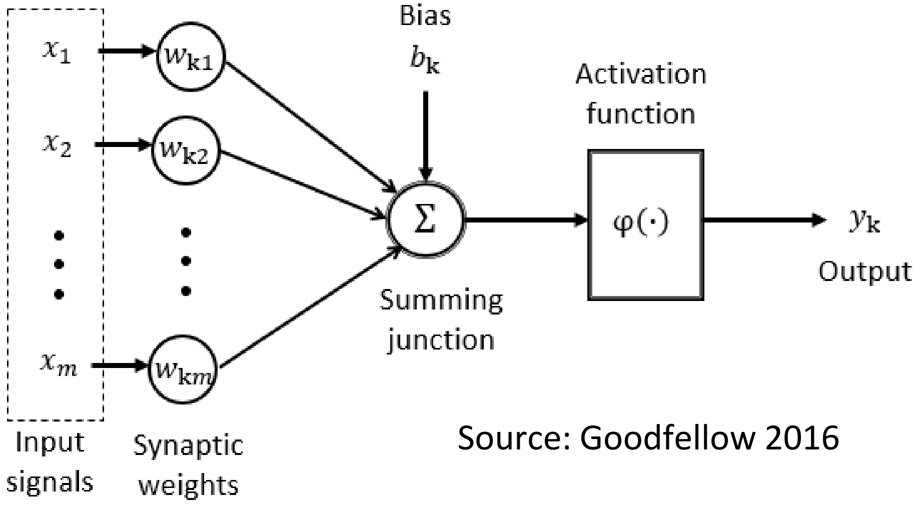
1. AHRI 10-coefficient mapping

$$\dot{m}_{map} = M_1 + M_2 \cdot T_e + M_3 \cdot T_c + M_4 \cdot T_e^2 + M_5 \cdot (T_e \cdot T_c) + M_6 \cdot T_c^2 + M_7 \cdot T_e^3 + M_8 \cdot (T_e^2 \cdot T_c) + M_9 \cdot (T_e \cdot T_c^2) + M_{10} \cdot T_c^3$$

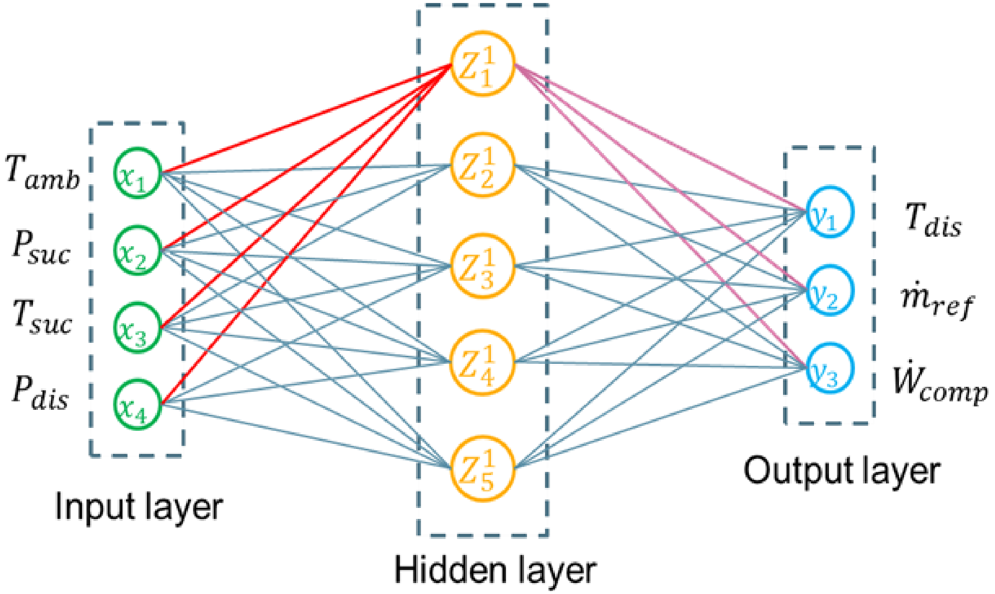
$$\dot{W}_{map} = P_1 + P_2 \cdot T_e + P_3 \cdot T_c + P_4 \cdot T_s^2 + P_5 \cdot (T_s \cdot T_d) + P_6 \cdot T_d^2 + P_7 \cdot T_s^3 + P_8 \cdot (T_s^2 \cdot T_d) + P_9 \cdot \left(T_s \cdot T_d^2\right) + P_{10} \cdot T_d^3$$

2. ANN models

$$y_k = \sum_{j=1}^{N_{neural}} \left(\omega_{kj}^{(2)} \varphi \left(\sum_{i=1}^{N_{input}} \omega_{ji}^{(1)} \cdot x_i + b_j^{(1)} \right) + b_k^{(2)} \right)$$



Source: Goodfellow 2016



Example of a compressor (single hidden layer)

Model Structures (cont'd)

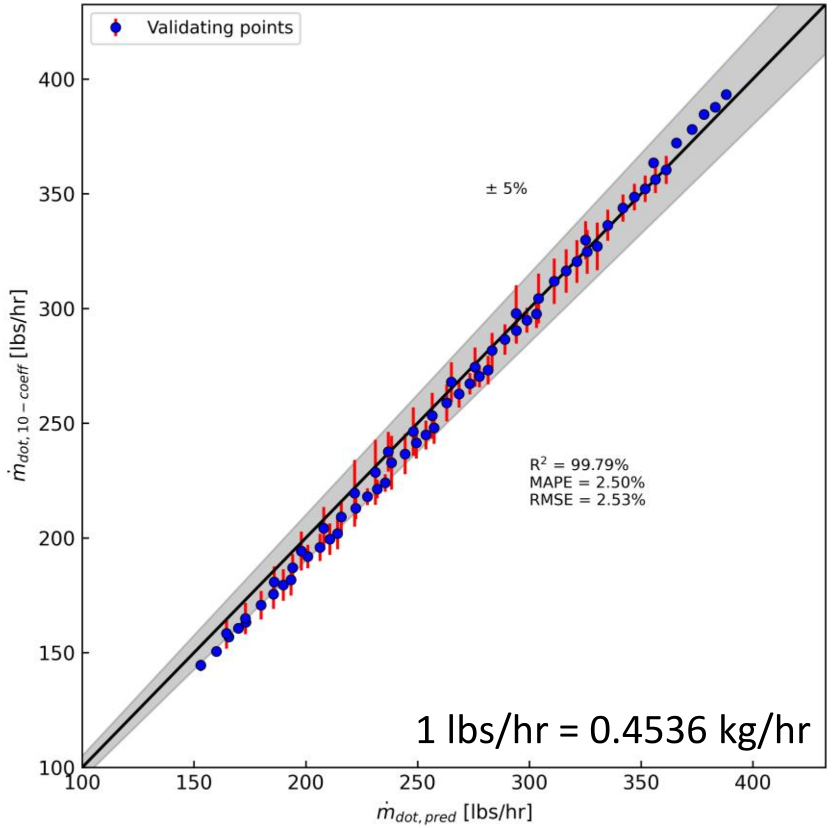
3. Gaussian Process (GP) regression

- Gaussian Process regression is "Bayesian regression on steroids" and allows uncertainty quantifications
- The target function $f(\cdot)$ is approximated has a mean function $m(\cdot)$ and a covariance function $k(\cdot,\cdot)$. The mean function $m(\cdot)$ is the expected value of the target function $f(\cdot)$
- The covariance function (or covariance kernel) $k(\cdot,\cdot)$ defines a nearness or similarity measure on the input space
- $\mathrm{X} \sim \mathrm{N}(\mu,\ \sigma^2) \ \rightarrow \ f(\cdot) \sim (m(\cdot), k(\cdot,\cdot))$
- The target function $f(\cdot)$ is assigned for a probability measure $P(f(\cdot))$ called prior probability measure. With training data, a probability measure $P(\mathcal{D} \mid f(\cdot))$ called posterior probability measure can be observed;
- By applying Bayes' rule, a probability measure of the ground truth function can be obtained:

$$P(f(\cdot) \mid \mathcal{D}) = P(\mathcal{D} \mid f(\cdot)) \times P(f(\cdot))$$

- The 95% confidence interval of the result probability measure of $f(\cdot)$ is used to represent the uncertainty of the model.

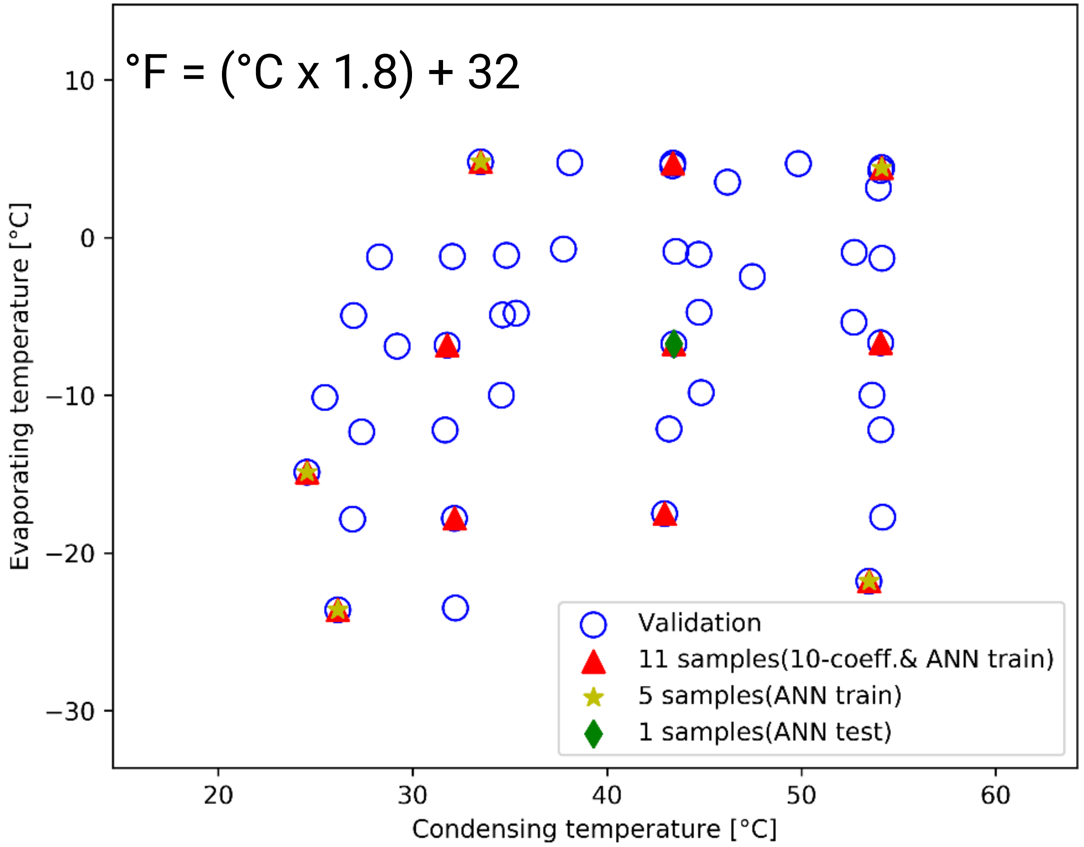
Scroll compressor with R410A



Source: Cheung et al. 2018

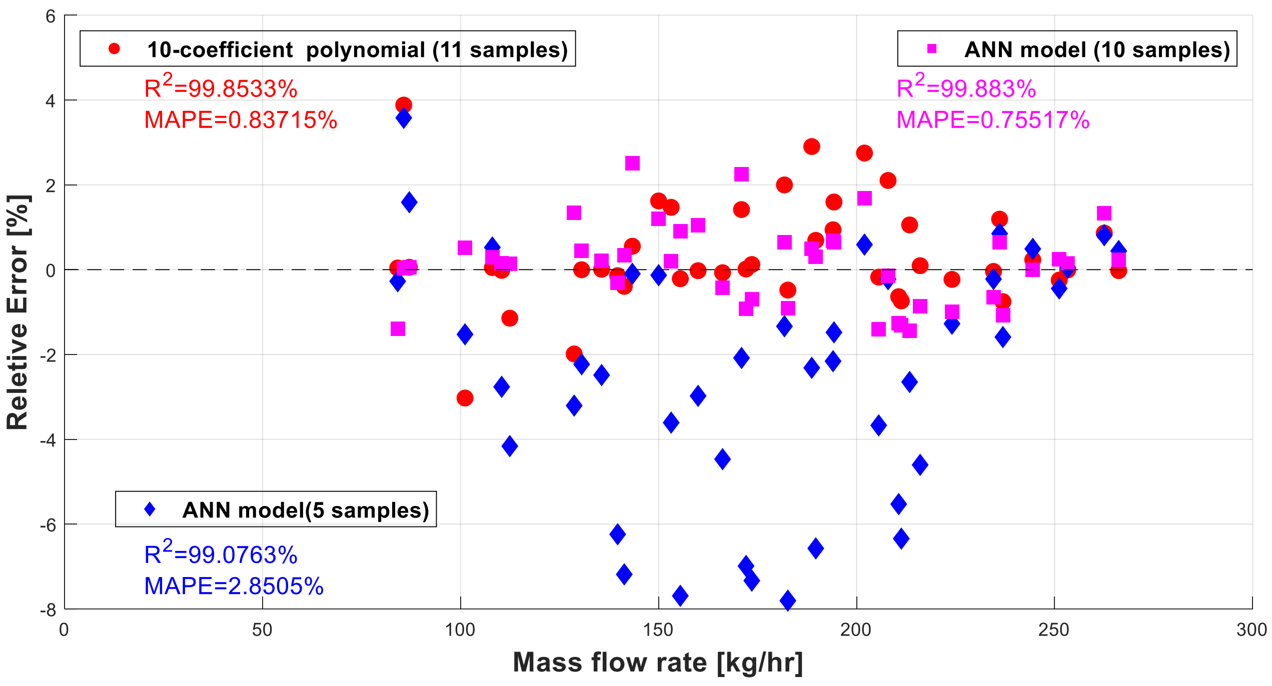
Case Study: ANN Model Structure

- Hermetic dual-cylinder rolling-piston compressor with R410A as the working fluid.
- A total of 43 steady-points were collected by colorimeter testing to train and validate the models.

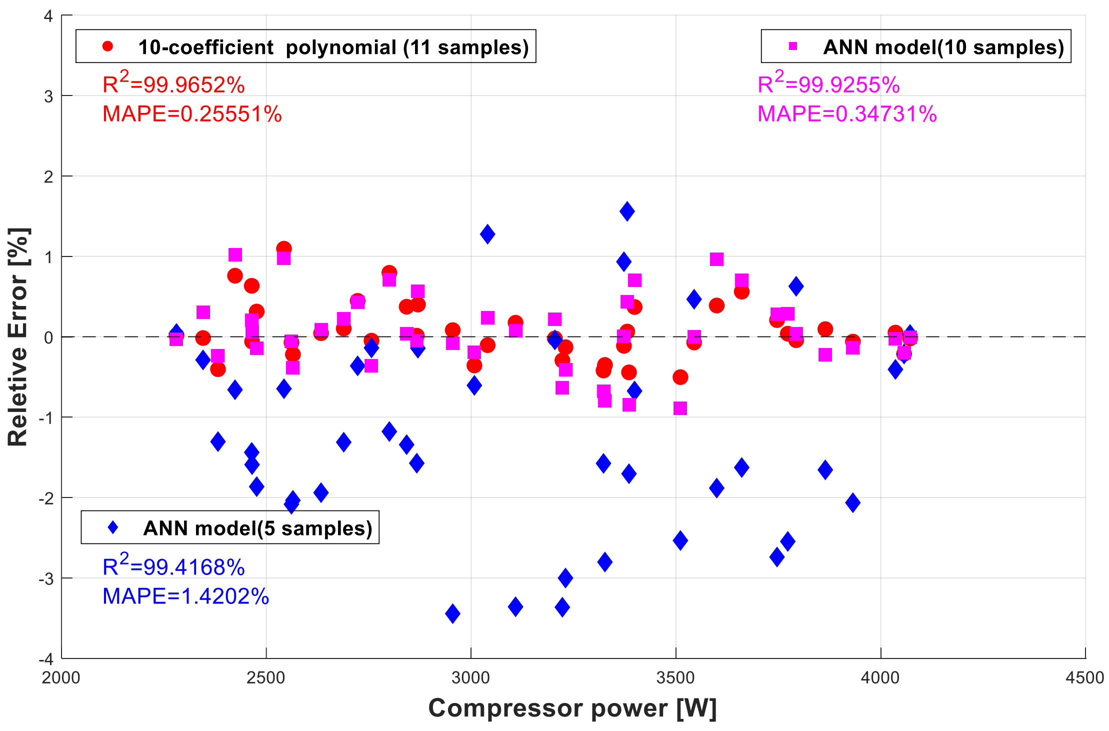


Case Study: ANN Model Structure (cont'd)

- Comparison AHRI 10-coeff. mapping vs. ANN



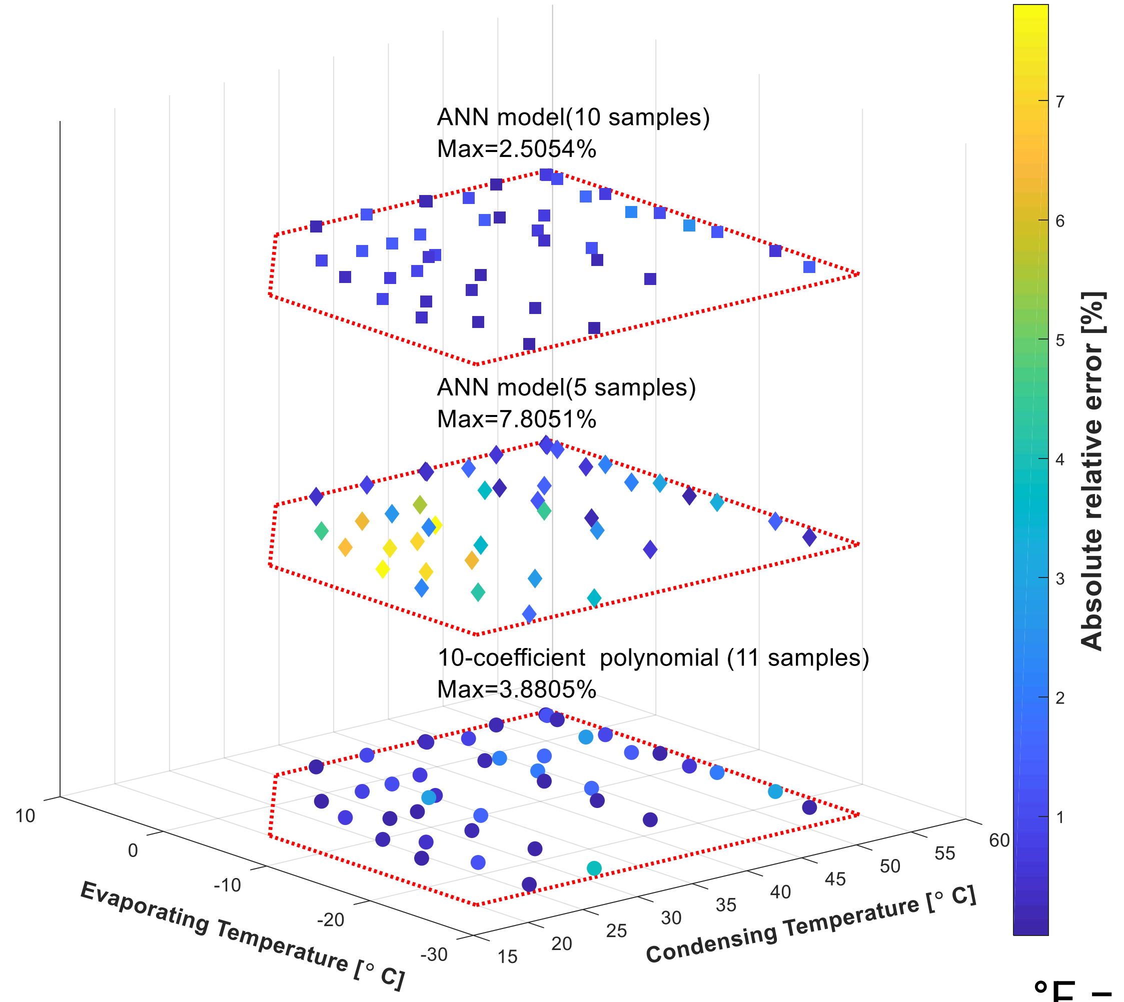
1 lbs/hr = 0.4536 kg/hr



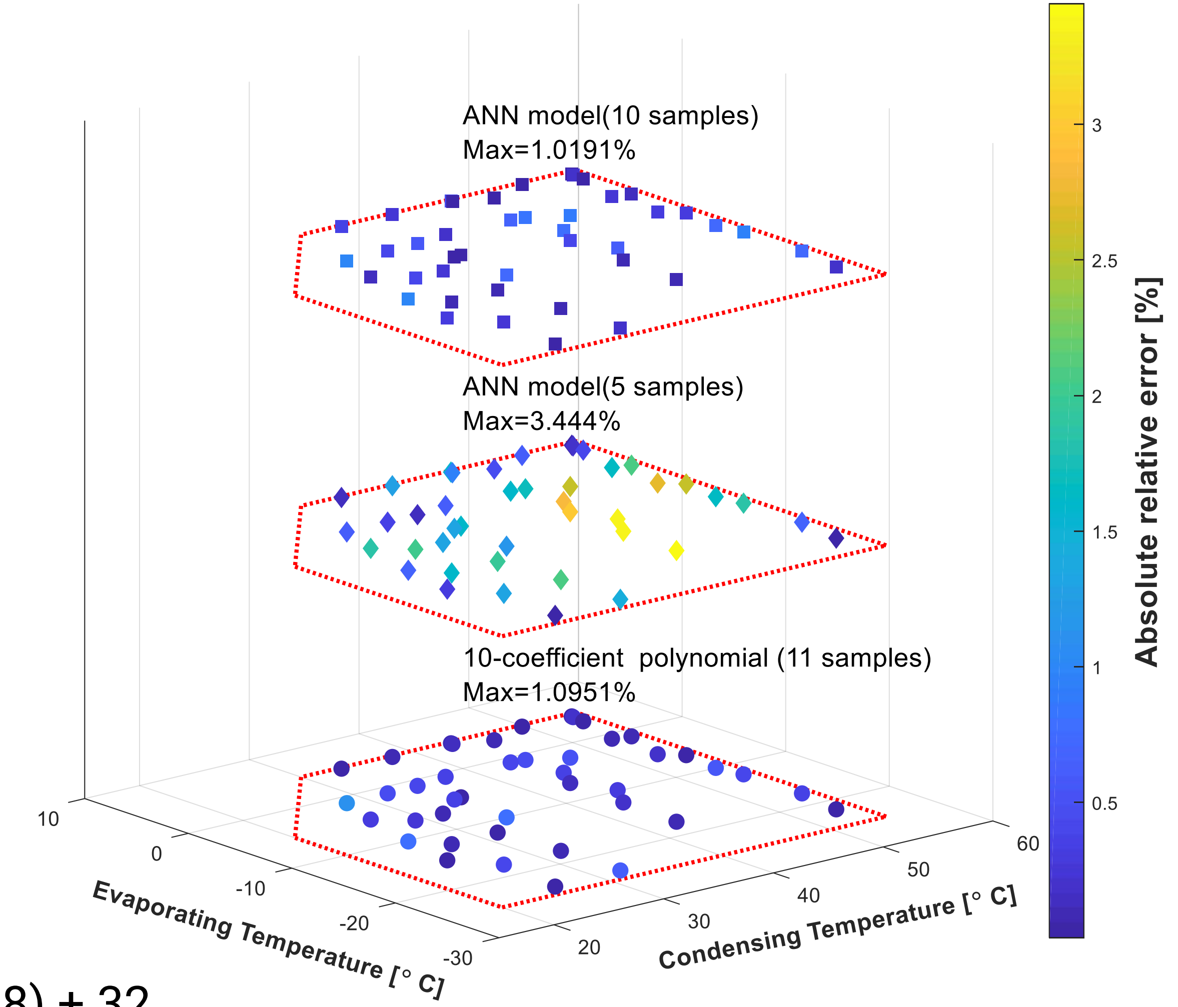
1 kW = 0.948 Btu/s

Case Study: ANN Model Structure (cont'd)

Mass Flow Rate



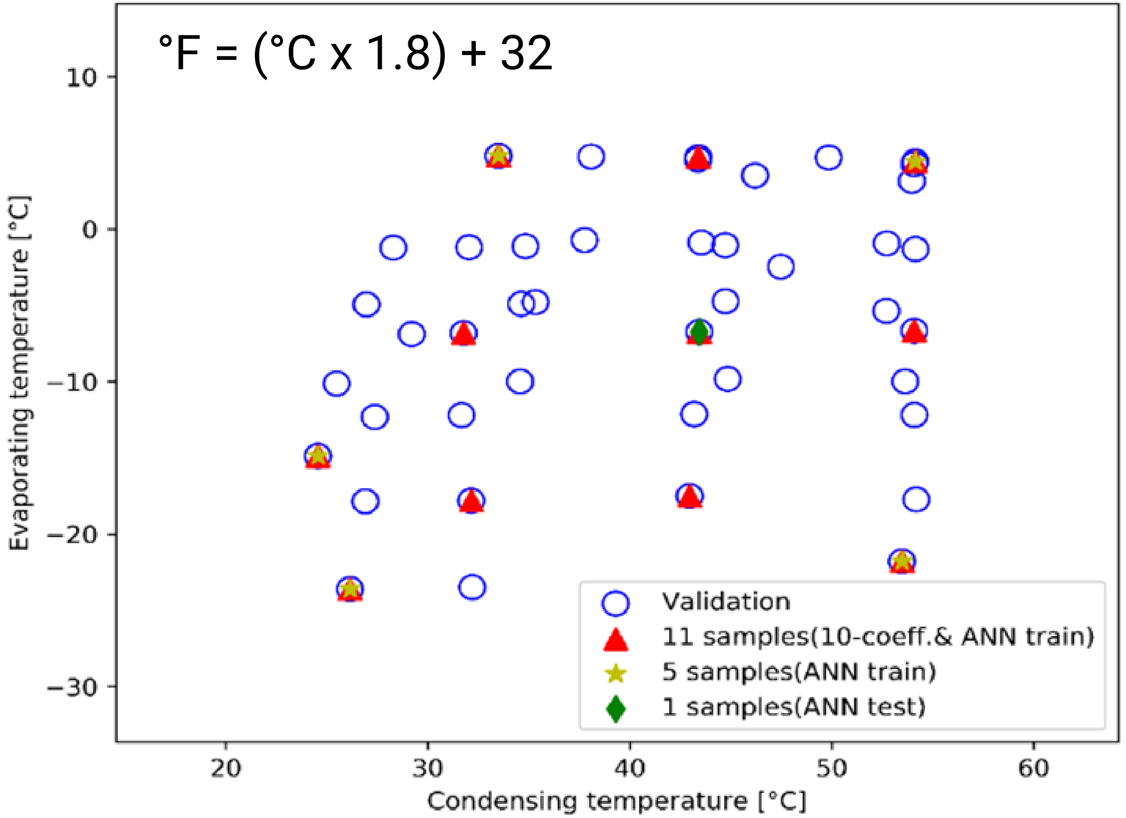
Compressor Power



°F = (°C x 1.8) + 32

Case Study: Uncertainty and Extrapolation Studies

- Hermetic dual-cylinder rolling-piston compressor with R410A as the working fluid.
- A total of 43 steady-points were collected by colorimeter testing to train and validate the models.



Uncertainty Analysis

1. AHRI 10-coefficient mapping (Reference: Cheung et al. 2018)

$$\Delta\hat{\dot{m}}_r = \sqrt{\left(\frac{\partial\hat{\dot{m}}_r}{\partial T_e}\right)^2 \cdot \Delta T_e^2 + \left(\frac{\partial\hat{\dot{m}}_r}{\partial T_c}\right)^2 \cdot \Delta T_c^2}$$

$$\Delta\hat{\dot{W}}_{comp} = \sqrt{\left(\frac{\partial\hat{\dot{W}}_{comp}}{\partial T_e}\right)^2 \cdot \Delta T_e^2 + \left(\frac{\partial\hat{\dot{W}}_{comp}}{\partial T_c}\right)^2 \cdot \Delta T_c^2}$$

T_e and T_c are dew−point temperatures which are calculated by the measured suction and discharge pressure. The uncertainty of pressure measurement ($\Delta P_{suc,mea}$, $\Delta P_{dis,mea}$) and uncertainty due to equation of state (EOS) is calculated:

$$\Delta T_e = \sqrt{\left(\frac{\partial T_e(P_{suc,mea})}{\partial P}\right)^2 \cdot \left(\Delta P_{suc,mea}^2 + \Delta P_{EOS}^2\right)}; \quad \Delta T_c = \sqrt{\left(\frac{\partial T_c(P_{dis,mea})}{\partial P}\right)^2 \cdot \left(\Delta P_{dis,mea}^2 + \Delta P_{EOS}^2\right)}$$

Uncertainty Analysis (cont'd)

2. ANN Model

$$\Delta\hat{\dot{m}}_r = \sqrt{\left(\frac{\partial\hat{\dot{m}}_{comp}}{\partial T_{amb}}\right)^2 \cdot \Delta T_{amb,mea}^2 + \left(\frac{\partial\hat{\dot{m}}_{comp}}{\partial P_{suc}}\right)^2 \cdot \Delta P_{suc,mea}^2 + \left(\frac{\partial\hat{\dot{m}}_{comp}}{\partial T_{suc}}\right)^2 \cdot \Delta T_{suc,mea}^2 + \left(\frac{\partial\hat{\dot{m}}_{comp}}{\partial P_{dis}}\right)^2 \cdot \Delta P_{dis,mea}^2}$$

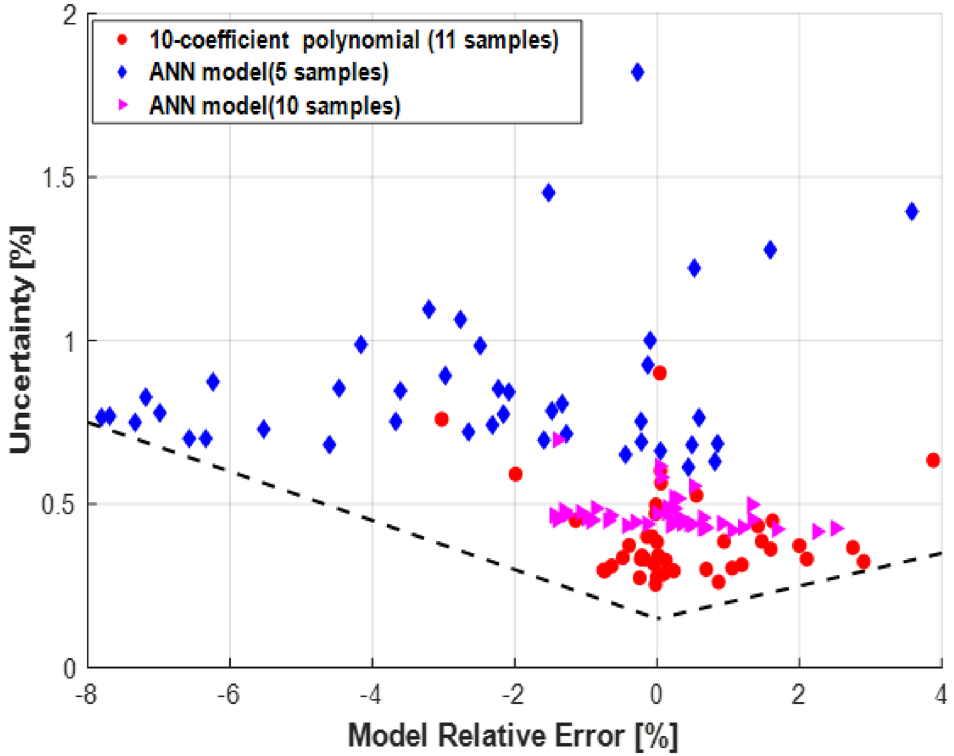
$$\Delta\hat{\dot{W}}_{comp} = \sqrt{\left(\frac{\partial\hat{\dot{W}}_{comp}}{\partial T_{amb}}\right)^2 \cdot \Delta T_{amb,mea}^2 + \left(\frac{\partial\hat{\dot{W}}_{comp}}{\partial P_{suc}}\right)^2 \cdot \Delta P_{suc,mea}^2 + \left(\frac{\partial\hat{\dot{W}}_{comp}}{\partial T_{suc}}\right)^2 \cdot \Delta T_{suc,mea}^2 + \left(\frac{\partial\hat{\dot{W}}_{comp}}{\partial P_{dis}}\right)^2 \cdot \Delta P_{dis,mea}^2}$$

The partial derivative of an output with respect to an input is calculated based on the neural network mathematical expression:

$$\left(\frac{\partial\, Y(k)}{\partial\, X(i)}\right)^2 = \left(\sum_{j=1}^{N_{neural}} \left(\omega_{kj}^{(2)} \cdot \omega_{ji}^{(1)} \cdot \frac{\partial\varphi}{\varphi x(i)}\right) \cdot \frac{\mathrm{Y}_{\max}(k) - \mathrm{Y}_{\min}(k)}{\mathrm{X}_{\max}(i) - \mathrm{X}_{\min}(i)}\right)^2$$

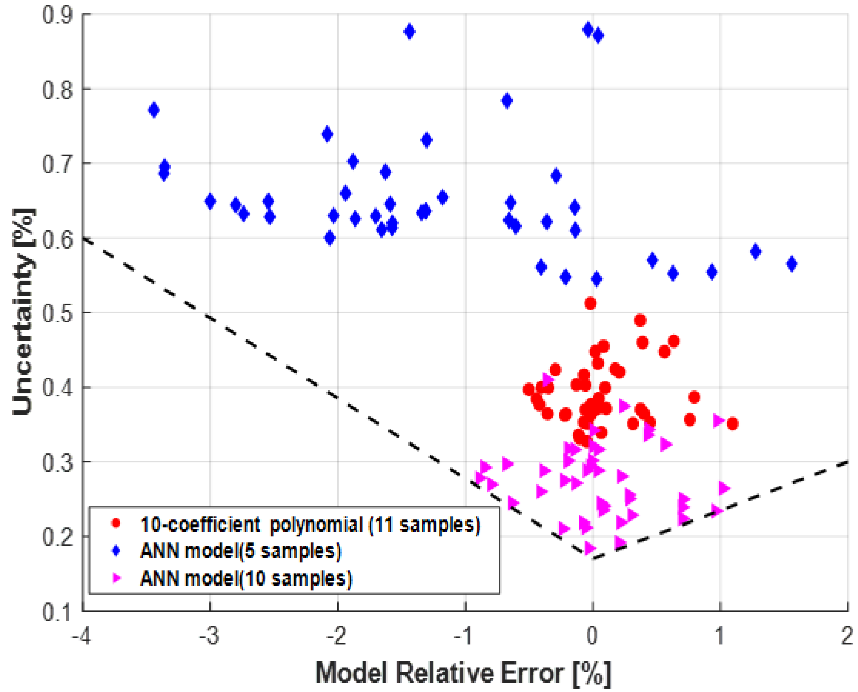
Uncertainty Analysis (cont'd)

Mass Flow Rate



Relative Error	Highest	ANN model (5 samples)
	Lowest	ANN model (10 samples)
Uncertainty	Highest	ANN model (5 samples)
	Lowest	10-coefficient polynomial

Compressor Power

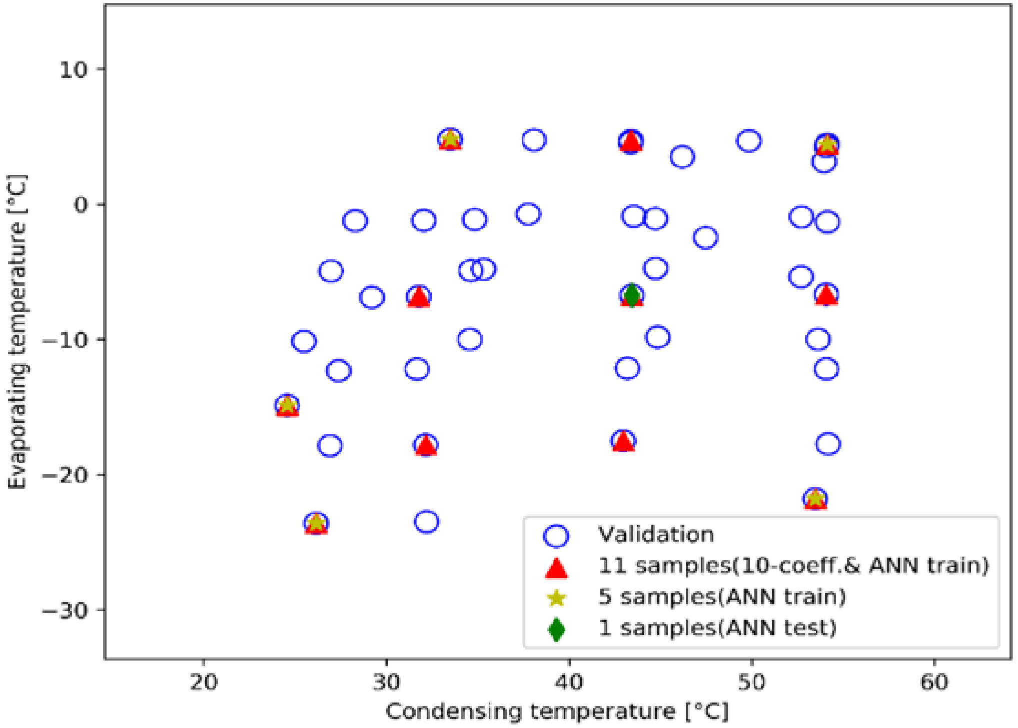


Relative Error	Highest	ANN model (5 samples)
	Lowest	ANN model (10 samples)
Uncertainty	Highest	ANN model (5 samples)
	Lowest	ANN model (10 samples)

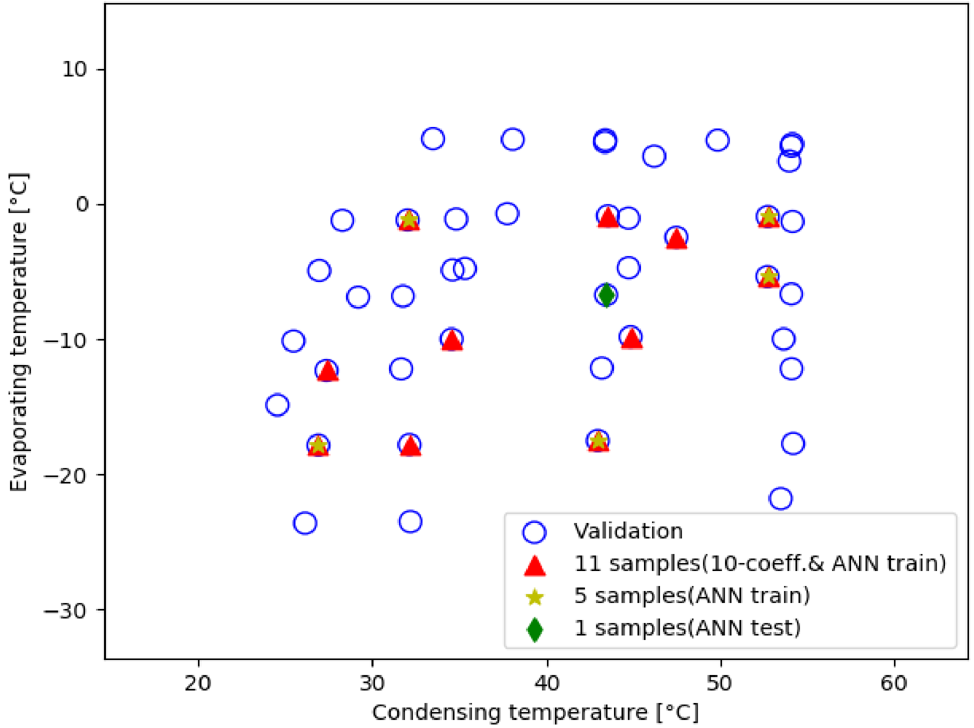
Extrapolation Analysis

- The new training data is selected within the compressor envelope.
- The data points outside the training data set are validation data points for extrapolation capabilities analysis.

Training samples on compressor envelope



Training samples within compressor envelope

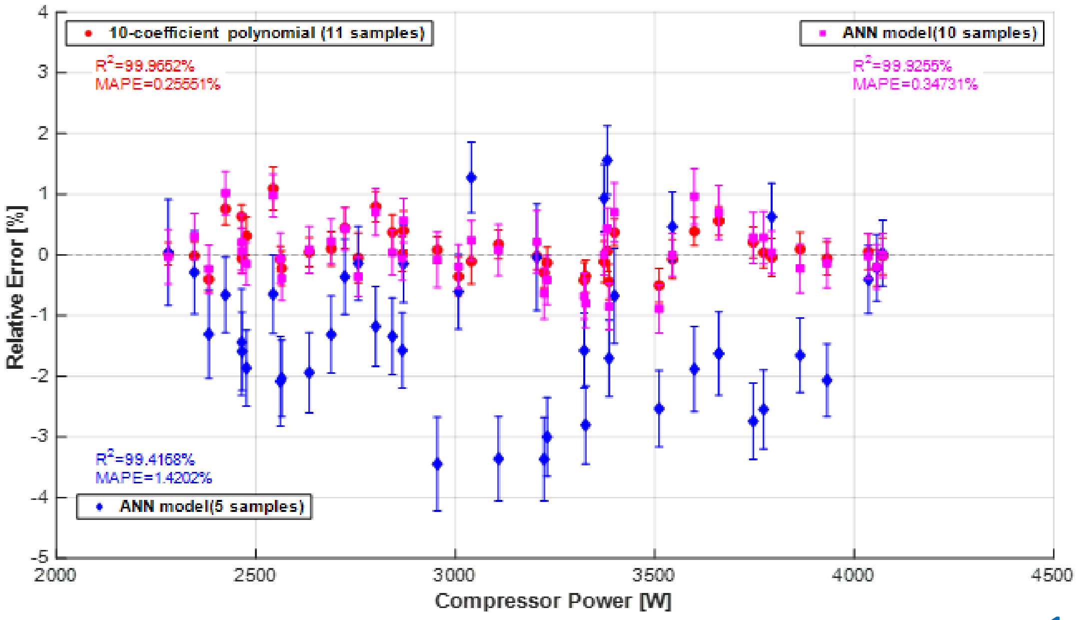


°F = (°C x 1.8) + 32

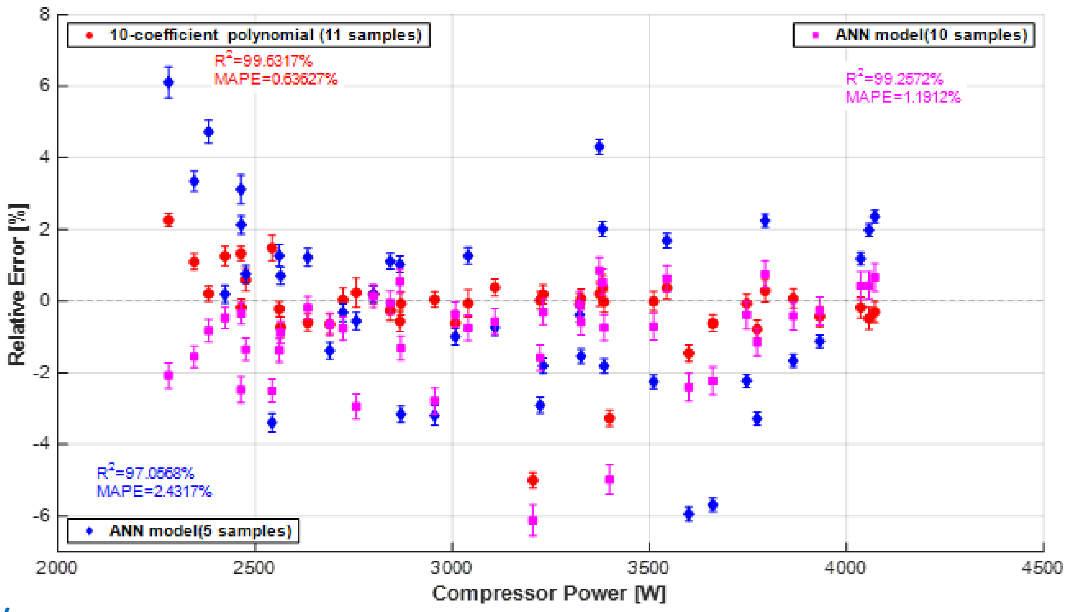
Extrapolation Analysis (cont'd)

	Training samples on compressor envelope		Training samples within compressor envelope	
	R^2	$MAPE$	R^2	$MAPE$
ANN model (5 training samples)	99.41%	1.42%	97.05%	2.43%
ANN model (10 training samples)	99.92%	0.35%	99.26%	1.19%
10-Coefficient polynomial	99.96%	0.251%	99.61%	0.64%

Training samples on compressor envelope



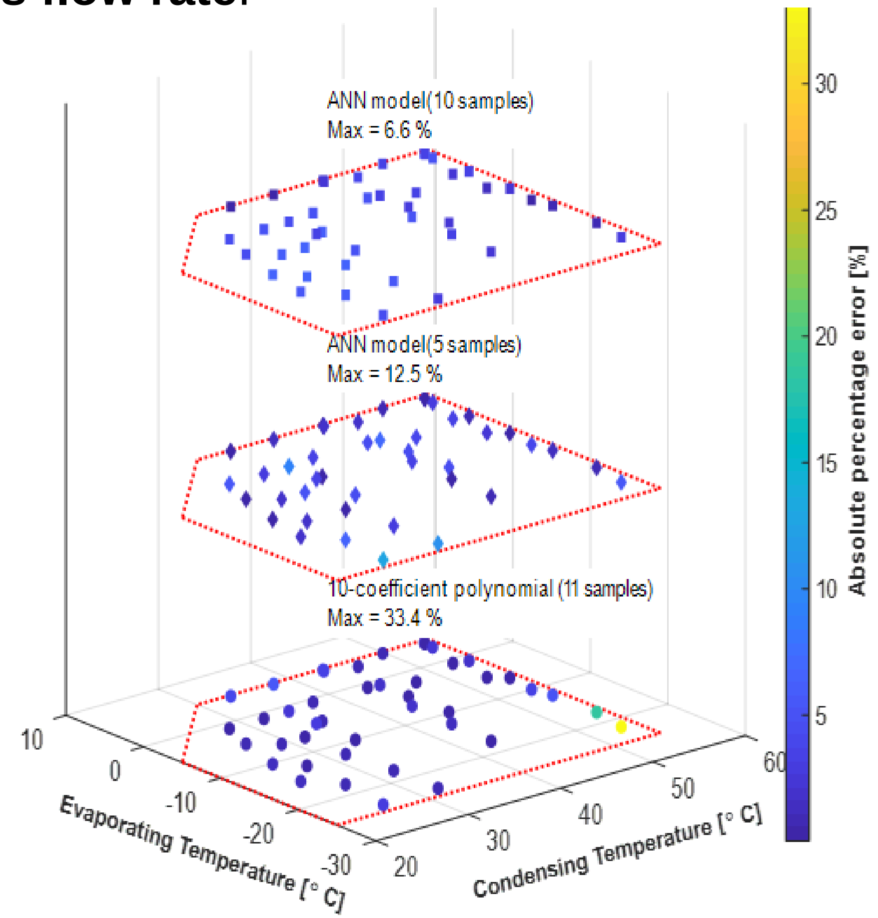
Training samples within compressor envelope

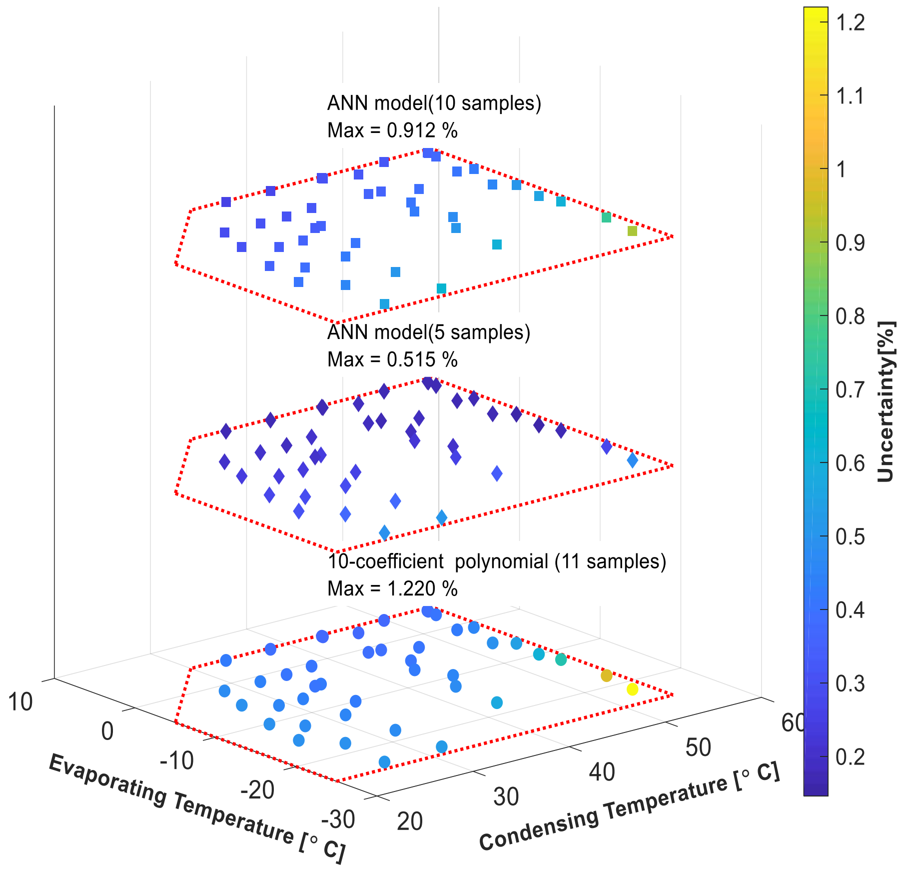


1 kW = 0.948 Btu/s

Extrapolation Analysis (cont'd)

- To clearly locate the position of data samples representing larger model relative error or higher uncertainty of **mass flow rate**:

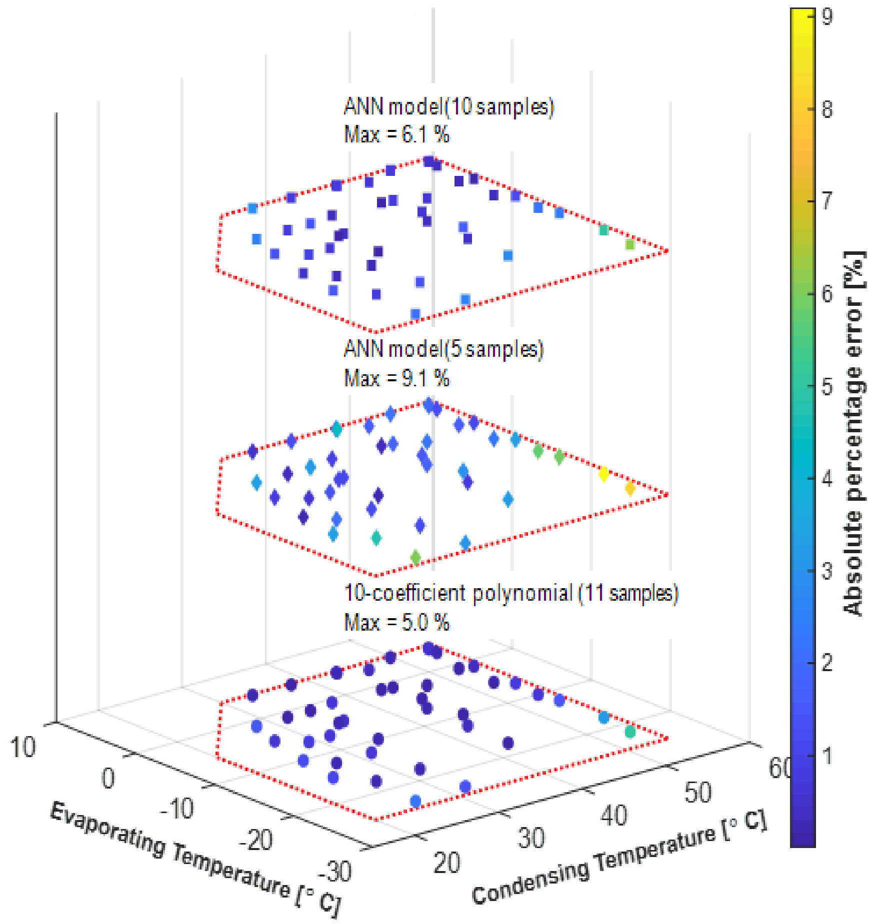


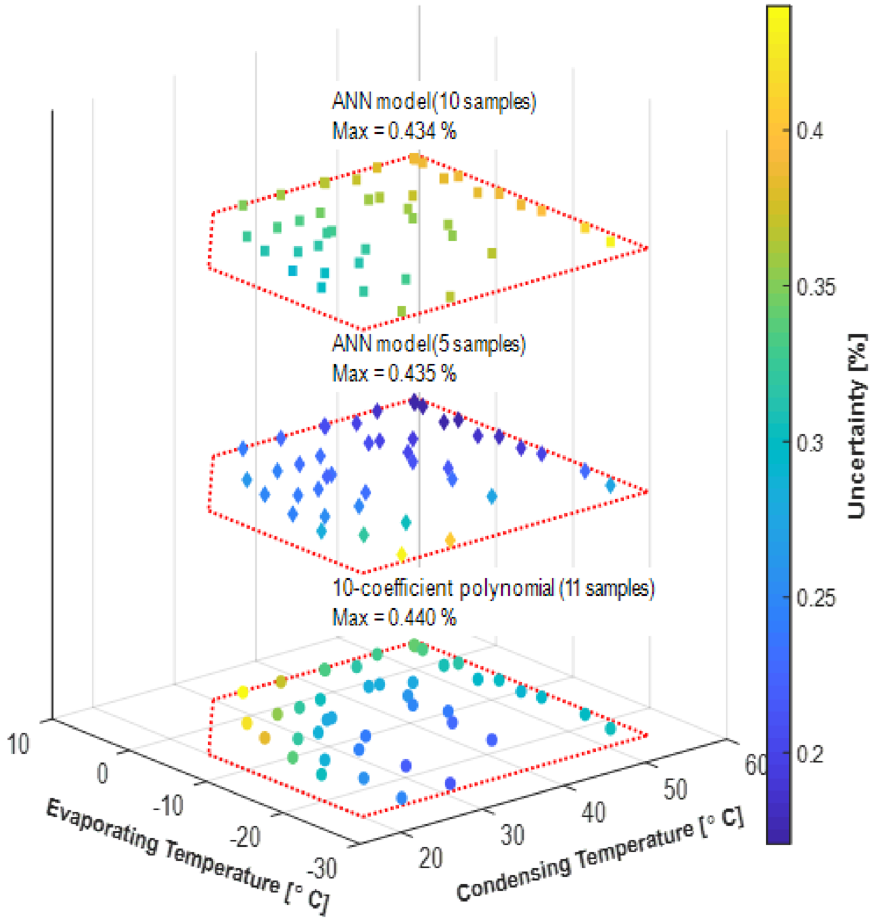


°F = (°C x 1.8) + 32

Extrapolation Analysis (cont'd)

- To clearly locate the position of data samples representing larger model relative error or higher uncertainty of **compressor power**:



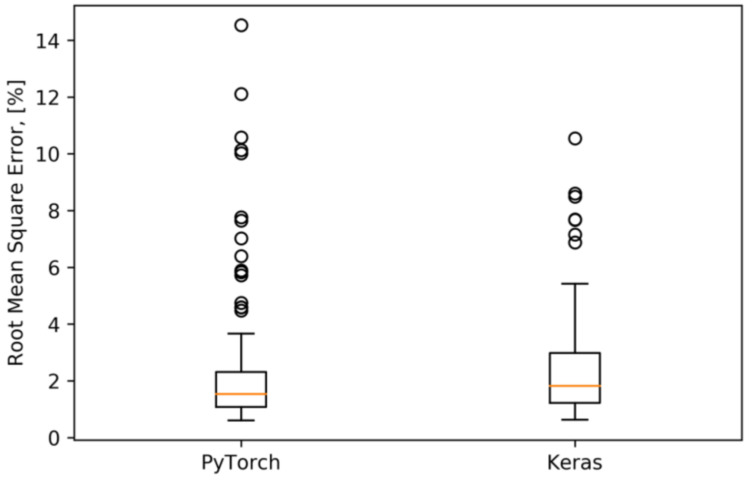


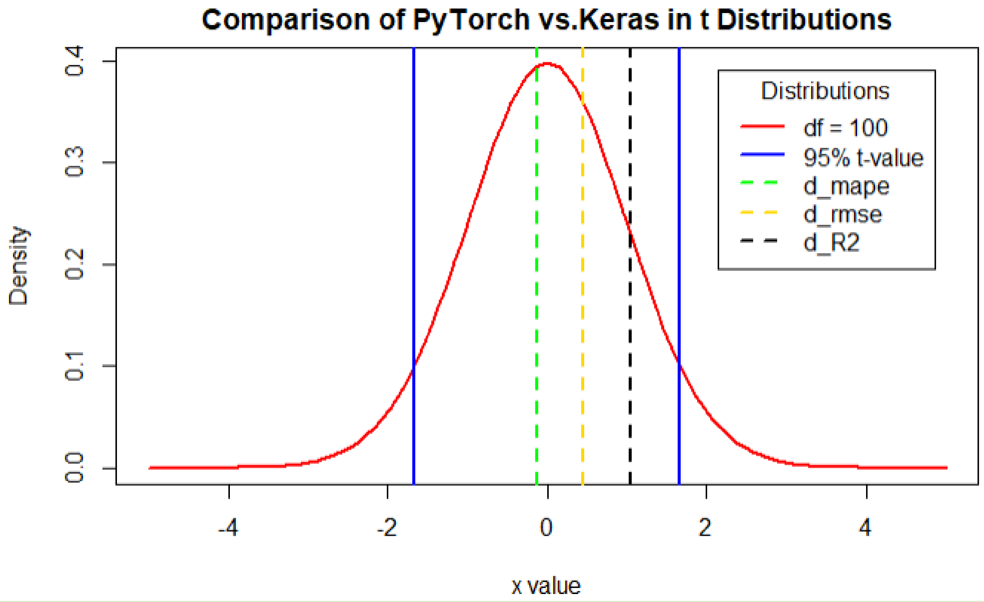
°F = (°C x 1.8) + 32

Conclusion

- What is the role of data-driven models for compressor mapping?
  - Data-driven models offer the opportunity of predicting performance based on data independently from the compressor technology
  - Several challenges can be identified:
    - Selection of data set, ML model
    - Degree of randomness during the training
    - Extrapolation beyond training space

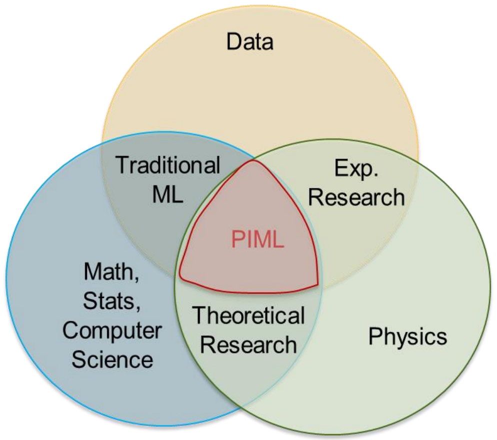
Reciprocating compressor dataset: a statistical comparison between Keras & PyTorch (based on 100 time iterations of each model)

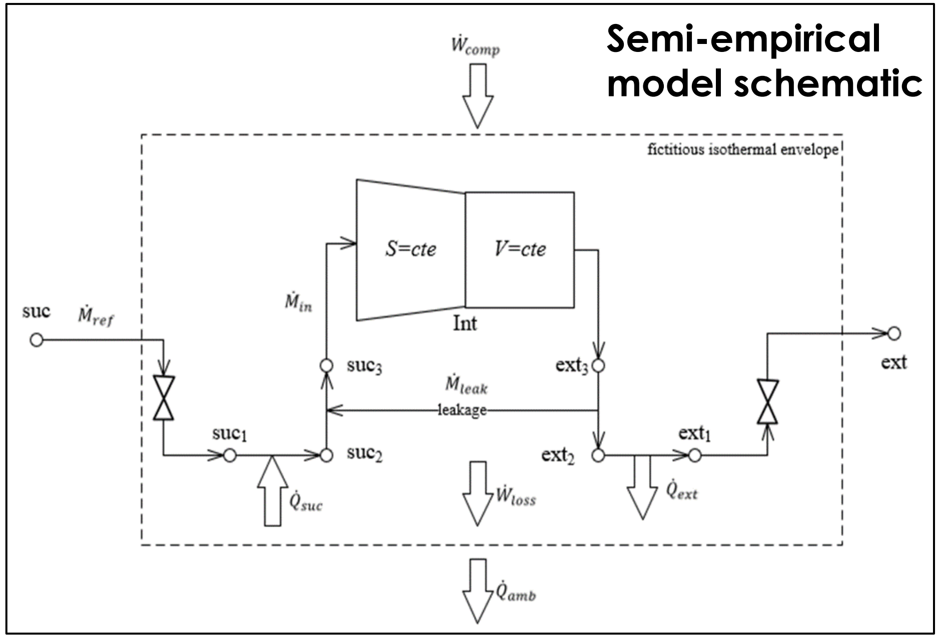




Conclusion (cont'd)

- What is the role of data-driven models for compressor mapping?
  - Physics-Informed Machine Learning (PIML):
    - Offers pathway to train a neural network in a supervised way on limited experimental datasets while respecting laws of thermodynamics/physics
    - Enable "smart" compressors:
      - Actively learn in-system performance from mapped performance
      - Load-based testing compressor mapping
      - FDD implementation and performance degradation
    - Combination of semi-empirical models and ML models





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Questions?

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