Predicting Vapor Injected Compressor Performance Using Artificial Neural Networks

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ABSTRACT

Positive displacement compressors have recently begun to include vapor injection more frequently to adapt to energy efficiency and decarbonization goals. High-accuracy models are crucial to predict the compressor performance for rapid integration into HVAC&R systems. Most existing empirical models use more than 10 experimental data points for accurate performance prediction, which can prove burdensome. This study aims to address the need for more universal and versatile compressor mapping methodologies that do not require such intensive and expensive experimental testing. An artificial neural network (ANN) based vapor-injected compressor performance mapping approach is proposed. The proposed ANN model architecture comprises of one input layer, one output layer, and one hidden layer. Input layer includes input parameters such as compressor speed, and suction, injection, and discharge pressures while output layer includes output parameters such as evaporator mass flow rate, injection mass flow rate, compressor power, and discharge temperature. In addition, this study qualifies the feasibility and reliability of the proposed ANN model using Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE). Data is collected on vapor injected scroll and rotary compressors with R410A and R454B to train and test the model. The model can predict the evaporator mass flow rate, injection mass flow rate, and compressor input power within 5% MAPE, and discharge temperature with 5K MAE.

1. INTRODUCTION

Improving heat pump performance remains a significant challenge in refrigeration research. Refrigerant injection has emerged as a key technical solution for air source heat pumps operating in regions with low ambient temperatures. Within such systems, refrigerant injection is categorized into vapor and liquid subgroups. Vapor injection, in particular, is employed to enhance cooling/heating capacity at the same compressor's stroke volume, presenting distinct advantages over liquid refrigerant injection (Xu et al. 2011). This technique has been extensively explored in various research published as a potential enhancement for air source heat pump systems.

Ma and Zhao, (2008) conducted an experimental investigation into the vapor injection heat pump cycle, incorporating a flash tank coupled with a scroll compressor. Wang et al. (2009) explored the performance of a 11kW R410A heat pump system employing a two-stage vapor injected scroll compressor through experimental means, thereby establishing fundamental design and operational guidelines for heat pump systems. Xu et al. (2011) extensively analyzed the performance disparity between R410A and R32 in a vapor-injected heat pump system utilizing a scroll compressor. Bertsch and Groll (2008) undertook simulation, design, construction, and testing of an air source two-stage heat pump system utilizing a scroll compressor under low ambient temperatures reaching -30 °C. Concurrently, similar experimental investigations of vapor-injected compressors showed enhanced performance, highlighting the significance of economization and vapor injection, as evidenced by a comprehensive review encompassing more than 50 papers (Yang et al. 2015, Cho et al., 2012, Khan and Bradshaw 2023).

Assessing the performance of vapor injection compressors constitutes a critical aspect of investigating the impact of injection on the system. Presently, two primary methods are employed for modeling compressor performance: efficiency methods based on the data collected from the experimental setups and detailed physics based models (Tanveer et al. 2022; Tanveer and Bradshaw 2021). However, unlike conventional scroll compressors devoid of injection, conventional efficiency models like the AHRI 10-coefficient model (Aute et al., 2015) are inadequate for representing the performance of injection scroll compressors due to the variable parameters associated with injected refrigerants. Consequently, researchers have extensively explored and applied either black box models tailored for vapor injection compressors (Tello-Oquendo et al., 2017) or comprehensive thermodynamic-principle-based models in predicting the performance of compressors (Bradshaw et al. 2016; Orosz et al. 2014; Islam et al. 2021).

The black-box model is one of the modelling approaches, which does not rely on specific physical information regarding compression and injection processes within the compressor. Instead, these models typically comprise polynomial equations, where the coefficients are adjusted to match experimental data. The primary challenge associated with black-box models is the issue of overfitting. Consequently, the model cannot predict the performance for unseen data and performs poorly in case of extrapolation (Hu et al. 2020). Black box models for vapor injected compressors in literature have been developed for scroll compressors (Tello-Oquendo et al. 2017b; Navarro et al. 2013, Khan and Bradshaw 2024b, Lumpkin et al. 2018).

In recent years, machine learning techniques and artificial intelligence methods have been utilized to accurately predict the performance of components or systems in different fields (Ledesma et al., 2015). In addition to all black-box models mentioned earlier, machine learning approaches such as artificial neural network (ANN), have been used for systems and compressor performance prediction in HVAC systems (J. Ma et al. 2020, Yousaf et al., 2022). With respect to positive displacement machines, Artificial Neural Network (ANN), Adaptive Neuro Fuzzy Interference System (ANFIS), and other hybrid approaches, e.g., ANN-PLS (Partial Least Squares), have been applied to characterize the performance of compressors such as reciprocating (Gabel and Bradshaw 2023, Ledesma et al., 2015).

The efficacy of artificial intelligence (AI) methodologies, in terms of both accuracy and computational efficiency, has been substantiated in the context of vapor compression systems. In the realm of compressor analysis, (Sanaye et al. 2011) developed an artificial neural network (ANN) approach tailored for a rotary vane compressor. This method leveraged inputs such as refrigerant suction temperature and pressure, compressor rotation speed, and refrigerant discharge pressure to predict the refrigerant mass flow rate and discharge temperature. Utilizing experimental data for model development, the ANN demonstrated superior performance compared to a nonlinear regression model. Similarly, Belman-Flores et al. (2015) employed ANN and physical models to estimate refrigerant mass flow rate, discharge temperature, and energy consumption for a reciprocating compressor. Inputs encompassed suction pressure, suction temperature, discharge pressure, and compressor rotation speed, with experimental data for R1234yf and R134a utilized for model validation. Tian et al. (2015) introduced a hybrid model, namely ANN-PLS, to forecast parameters such as volumetric efficiency, refrigerant mass flow rate, discharge temperature, and power consumption for a variable scroll compressor operating with R134a. This approach integrated inputs including evaporation temperature, condensing temperature, and compressor speed. Comparisons among the hybrid model, single ANN, and PLS models, based on analysis of 148 experimental datasets, revealed the superior accuracy of the ANN model. Consequently, it was deduced that the ANN outperformed alternative models under consideration.

To sum up, previous research has confirmed the possibility of applying artificial intelligence methods for the prediction of compressor performance. To the best of the authors' knowledge, there is still a lack of effective attempts to use artificial intelligence methods to predict the performance of the vapor injection compressors for multiple compressor technologies, which is currently in great need of a precise and fast predictive model for refrigeration or heat pump system research. Therefore, in the current paper, an approach is developed using an ANN model to accurately predict the performance of a vapor injected compressors by considering the rotational frequency (ω), suction, injection, and discharge pressure (P_{suc}, P_{inj}, P_{dis}) as the inputs. Additionally, there is a lack of literature regarding refrigerant-sensitive models, which can be trained using data for one refrigerant (such as R410A) and subsequently applied to predict the performance of a drop-in refrigerant (such as R454B) using the same model coefficients. In particular, the main contributions of the present work with respect to the available literature are as follows:

- To develop and validate an ANN model for the scroll and rotary compressor with refrigerants R410A, R454B, and R407C
- To assess the ability of the ANN to predict compressor performance on a different, yet thermodynamically similar, refrigerant than it was trained on.

2. EXPERIMENTAL DATA COLLECTION AND COMPILATION

Experimental data is compiled from 6 vapor injected compressors of 2 technology types (rotary and scroll), using 3 refrigerants for a total of 195 steady state data points to be used for model training and evaluation. The majority of this data is collected by the authors (116 data points), with supplemental data collected from the literature.

2.1 Experimental data collection – in house data

For the in-house data collection, the hot-gas bypass load stand has been used for collection of data on two scroll and rotary compressors with refrigerants, R410A and R454B. The load stand is capable of testing both traditional and economized compressors at saturated suction temperature as low as -34.44 ℃ (-30 °F) and saturated discharge temperature as high as 60 ℃ (140 °F). The design capacity for the load stand is 1-5 tons (3.52-17.5 kW) compressor capacity. Complete operational details and uncertainty of the load stand is presented in (Khan and Bradshaw 2024a). Performance data for two compressor technologies, scroll and rotary, are collected with two working fluids, R410A and R454B with a total of 116 data points. The compressors are commercially available hermetic compressors originally designed for operation with R410A. The scroll compressor has a rated capacity of 5 tons and the rotary 3.25 tons. The complete test matrix was developed based on one factor at a time design of experiments method. The final test matrix collected data at evaporating temperatures ranging from -34.44 ℃ to 10 ℃ (-30 °F to 50 °F), condensing ranging from 23.8 ℃ to 54.44 ℃ (75 °F to 130 °F), superheat from 2.8 ℃ to 16.7 ℃ (5 °F to 30 °F), and speeds from 1800 rpm to 6000 rpm.

Supplemental experimental data was also collected from literature including data for a scroll compressor from Dardenne et al. (2015) and (Tello-Oquendo et al. 2017b), both tested with R407C as shown in Table 1. A summary of the data sets for the analysis of the models with compressor type, refrigerant, number of data points, and collection standard is shown in Table 1. The full data set is then divided into two subsets for each model performance evaluation, training and testing data set. The training data is used to develop the network of the proposed model, while the testing data, which has not already been used in training, is employed to evaluate the generalization capability of the proposed model. Therefore, 80% of the whole data set was selected randomly and utilized to train model, while the remaining 20% was used to test the robustness of the proposed model.

Table 1: Compiled experimental data sets

Compressor Type	Capacity	Refrigerant	Data Points	Collection Standard
Rotary (In-House)	3.25 tons	R410A	29	ASHRAE 23.1
Rotary (In-House)	3.25 tons	R454B	29	ASHRAE 23.1
Scroll (In-House)	05 tons	R410A	29	ASHRAE 23.1
Scroll (In-House)	05 tons	R454B	29	ASHRAE 23.1
Scroll (Dardenne et al. 2015)	03 tons	R407C	63	ASHRAE 23.1
Scroll (Tello-Oqu. et al., 2017b)	4.74 tons	R407C	16	ISO

3. DEVELOPMENT OF ANN FOR VAPOR INJECTED COMPRESSORS

3.1 Artificial Neural Network (ANNs)

Artificial neural networks (ANNs) constitute predictive tools inspired by the functional principles of the human brain and serve as effective models particularly when the relationship between inputs and outputs is ambiguous (Uçkan et al. 2015). This methodology, extensively utilized for prediction, pattern recognition, and classification tasks, has garnered considerable attention (Kirişci and Simsek 2023). ANNs possess the capacity to discern and identify correlated patterns through training, subsequently facilitating the prediction of new values. The architecture of a basic ANN typically encompasses an input layer, a single hidden layer, and an output layer interconnected within the network. The number of neurons in the input and output layers corresponds to the dimensions of the input and output vectors, respectively, while the determination of neurons in the hidden layer often involves an iterative trial-and-error process (Ghiasi et al. 2016).

A schematic representation of an ANN neuron is presented in Figure 1. In this configuration, a set of inputs denoted as "n" is fed into the network. The performance of the network is contingent upon the weights and bias values associated with each neuron. The net input function "A" is generated by the multiplication of input values with corresponding weights, followed by the addition of bias. Subsequently, the output "S" is derived through the application of a transfer function to the resultant net function, as expressed mathematically below:

$$S = f(A) = f[\sum_{i=1}^{n} X_i w_i + b] \tag{1}$$

where "X" is the input variable, "w" denotes the weight, and "b" represents the bias.

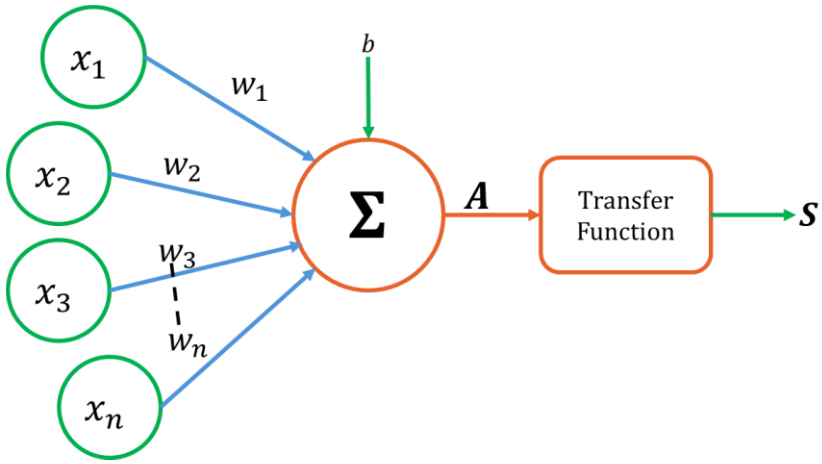

Figure 1: The model of ANN neuron.

During the training phase of the network, the predicted values generated by the ANN are compared with the actual values. The weights linked to each input are iteratively adjusted, either increasing or decreasing, in accordance with appropriate learning rules aimed at minimizing the disparity between desired and actual outcomes. This iterative process of training and weight adjustment is commonly referred to as the back-propagation algorithm. The updated weights are computed by the novel algorithm through the following formula:

$$w_{ij}^{\text{new}} = w_{ij}^{\text{old}} + \Delta w_{ij} \tag{2}$$

In backpropagation, the error is propagated backwards through the network and the objective of this propagation is the weights and biases adjustments. To minimize the loss, the weights are adjusted in the opposite direction of the gradient:

$$\Delta w_{ij} = -\eta \frac{\partial L}{\partial w_{ij}} N_j \tag{3}$$

where η stands for the learning rate, L stands for the loss function with respect to weights and N stands for the jth term.

This process continues for multiple epochs until the network converges, i.e., until the error is minimized, and the network learns to make accurate predictions on the training data. Briefly, the ANN approach follows the following steps to reach the target outputs from the assigned inputs:

- Select the inputs and outputs of the target problem.
- Collect the data and assign training and testing data.
- Define the architecture of the ANN by optimizing the hyperparameters.
- Evaluation of the target problem after training with training data set.

3.2 Application of ANN for Vapor Injected Compressors

The Artificial Neural Network (ANN) employs interconnected nodes, akin to the human brain's structure, to process numerical inputs. It optimizes its performance through an algorithm adjusting weights and biases via backpropagation. This iterative process minimizes the disparity between predicted and actual outputs, enhancing predictive accuracy. In this study, the Limited Memory Breydon-Flecher-Goldfarb-Shanno (lbfgs) optimizer is employed which is usually more stable, while the rectified linear activation function is used, which accurately and efficiently transforms negative inputs to zero and preserves positive values. The mean absolute percent error (MAPE) is selected as the loss function.

Four inputs, namely suction pressure, injection pressure, discharge pressure, and compressor speed, are fed into the network, while the network outputs are evaporator mass flow rate, injection mass flow rate, discharge temperature, and compressor power as shown in Figure 2. Each model comprises an input layer, a hidden layer, and an output layer. The ANN model provides different outputs when the number of neurons in the hidden layer changes, which can directly affect the generalization and approximation of the proposed model. In this regard, the number of neurons in the hidden layer is changed to achieve an optimum architecture. The dataset for model training consists of randomly selected data, with 80% allocated for training and 20% for testing. Due to the fact that the inputs of the ANN have different orders of magnitude, both training and testing data sets have been normalized between 0.1 and 0.9, as outlined in (J. Ma et al. 2020):

$$x_n = 0.8\frac{x-x_{min}}{x_{max}-x_{min}} + 0.1 \tag{4}$$

During training, the data is passed through the input layer, and the optimization algorithm is applied, after configuring the hyperparameters. It should be highlighted that, even if it is likely that a better result would be gained by using a high number of neurons, data over-fitting and an increase in computational time may occur. Therefore, a low number of neurons is preferable (Fatehi et al. 2014). Table 2 summarizes the artificial neural network architecture considered for this study.

Table 2: ANN model architecture, developed in Python

Parameters	**Values**
Machine Learning Package	Scikit-learn
Inputs	4
Outputs	2
Hidden Layers	1
Nodes Per Layer	45
Activation Function	Rectified Linear
Optimizer	Limited Memory BFGS

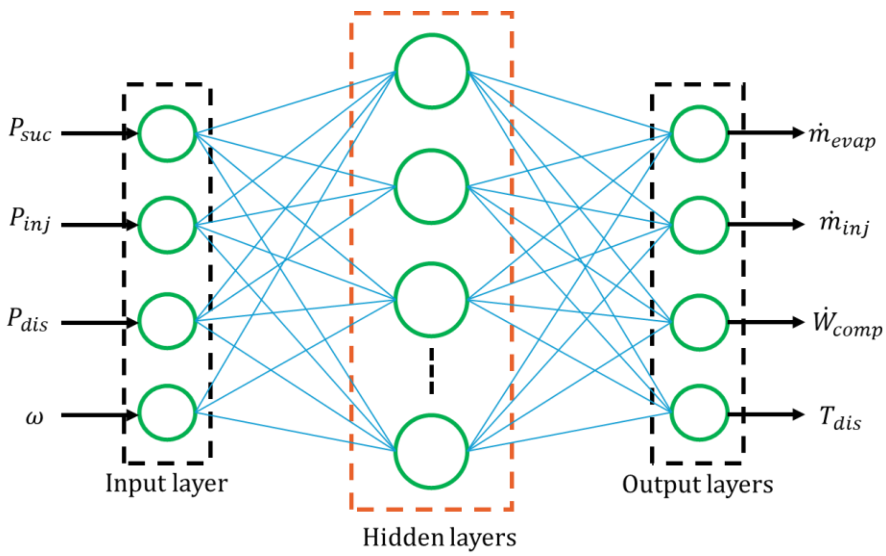

Figure 2: Schematic of ANN model

3.3 Error Metric to Evaluate Model Performance

The completed ANN is trained then evaluated for its ability to predict compressor power, evaporator, and injection mass flow rates using the method. The ANN model is initially trained using 80% of the dataset and kept same model architecture for fair comparison while evaluating performance for multiple compressor technologies and different refrigerants. Following the training phase, the performance of the trained model is evaluated by comparing its predictions against the corresponding test data obtained from experiments as described in Sections 2. The evaluation of model performance is quantified using the Mean Absolute Percentage Error (MAPE), which serves as a metric to measure the accuracy and effectiveness of the models in predicting the desired outcomes,

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{Y_{true,i} - Y_{predict,i}}{Y_{true,i}} \right|, \quad (5)$$

where n is the total number of data points in the data set, i is each data point, $Y_{true,i}$ and $Y_{predict,i}$ are the model measured data value and model predicted data value for any performance parameter. The MAPE is calculated for both the evaporator and injection mass flow rates as well as compressor power.

The Mean Absolute Error (MAE) is a metric used to evaluate the accuracy of a regression model. It measures the average absolute difference between the actual and predicted values. In this paper, MAE is used to calculate the error difference of temperature in Kelvin. The formula for calculating the Mean Absolute Error is:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|, \quad (6)$$

Where n stands for number of samples, y_i stands for the actual value of target variable, $\hat{y}_i$ stands for the predicted value of target variable. MAE is used to calculate the absolute differences between the actual and predicted values across all samples in the dataset specifically used for temperature.

4. RESULTS AND DISCUSSION

In the current study, ANN was developed and introduced for the fast and accurate estimation of the parameters of a vapor injected compressor working with refrigerants R410A, R454B, and R407C. To highlight the merits of the proposed model, 4 parameters, namely ω, P_{suc}, P_{inj}, and P_{dis}, were considered as the inputs of the model, while $\dot{m}_{evap}$, $\dot{m}_{inj}$, $\dot{W}_{comp}$, and T_{dis} were the outputs.

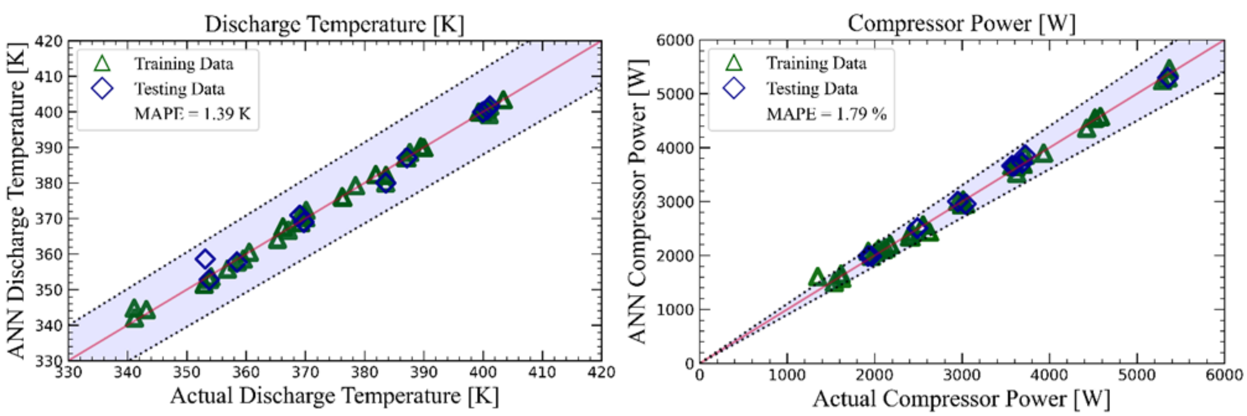

Figure 3: ANN Results for Compressor Power (right) and Discharge Temperature (left)

In the ANN network, the number of neurons in the hidden layer changed between 1 and 45. According to MAPE values analyzed, based on normalized data, the increase in the number of neurons from 1 to 45 brings a satisfactory result, so overall 45 neurons were selected in 1 hidden layer due to higher accuracy of the model with lowest MAPE values for the output parameters. A comparison between actual and predicted data using the developed approach is presented and discussed in the following in detail to evaluate the proficiency of the ANN model. It is worth noting that plots in Figures 3 and 4 are extracted using the readily available data in literature from (Dardenne et al., 2015).

Figure 3 show regression plots of the compressor power and compressor discharge temperature predicted by ANN with respect to actual values of the data. In these figures, the predicted data are plotted on the vertical axes as a function of the actual values. As clearly seen, almost all of the points are along a straight line, which highlights the reliability of the ANN model in prediction of compressor power and compressor discharge temperature. As depicted from Figure 3, the MAPE value for the compressor power consumption is less than 2% and MAE for the discharge temperature is 1.39K, showing the superior predictive capability of ANN model.

Figure 4 illustrates the regression plots of the evaporator and injection mass flow rate predicted by ANN plotted on the vertical axes against the actual values on the horizontal axes, respectively. Based on the results, the outcomes of ANN are linearly aligned, confirming the suitability of the proposed ANN model for the prediction of evaporation and injection mass flow rate. The MAPE in case of evaporator mass flow rate is less than 1%, while in case of injection mass flow rate prediction is almost 2%.

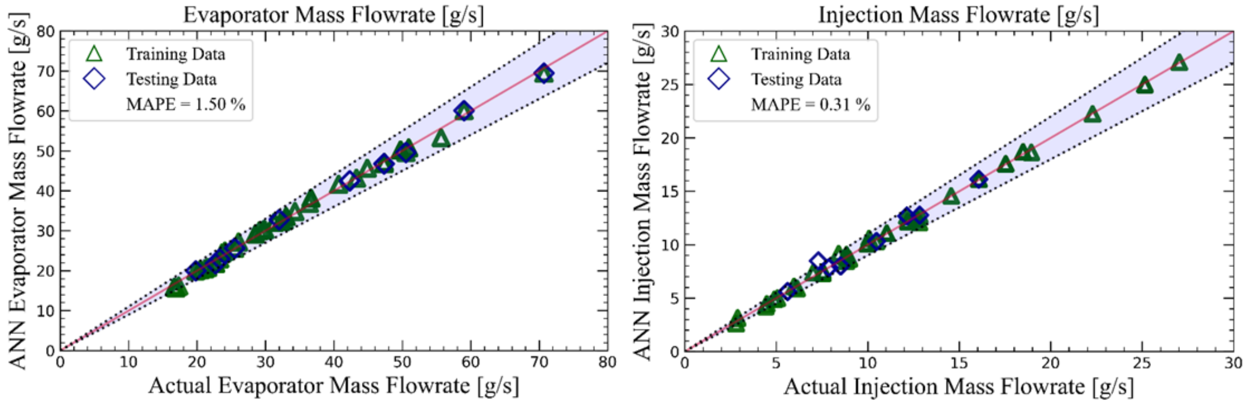

Figure 4: ANN results for Evaporator (left) and Injection Mass Flow Rate (right)

MAPE and MAE, for each model predicted parameter is summarized in Table 3. As is evident from the Table, the MAPE values are in the range of 1-2% for compressor power and mass flow rates, while in case of discharge temperature, the MAE values are in the range of 1-2 K, except for few cases in which it exceeds the mentioned ranges, showing the significance of ANN and its predictive capability. Aside from the good predictive capability of ANN, it is worth noting that choosing the number of nodes, number of hidden layers, activation function, and solver is very critical in special cases like compressors and their systems. The wrong selection of any of these hyperparameters will result in over-fitting and/or poor predictions.

Table 3: Summary of ANN model results

Datasets	MAPE (%) $\dot{W}_{comp}$	MAPE (%) $\dot{m}_{evap}$	MAPE (%) $\dot{m}_{inj}$	MAE (K) T_{dis}
Rotary R410A	0.98	0.97	1.498	0.985
Rotary R454B	1.04	1.1	1.872	1.024
Scroll R410A	1.4	0.8	2.212	1.354
Scroll R454B	2.4	1.6	2.57	1.824
Tello-Oq.	0.34	0.55	0.478	NA
Dardenne	0.67	0.784	2.175	1.018

4.3 Refrigerant Sensitivity Analysis

Refrigerant sensitivity analysis is the analysis in which a proposed model is trained with the training data of one refrigerant (R410A) and uses the trained model to predict the performance of the testing data set of a drop-in refrigerant (R454B). In this study, refrigerant sensitivity analysis was assessed for all output parameters. The in-house experimental data obtained for this study includes identical datasets for both R454B and R410A on two compressors, a scroll and a rotary. These results were used to train model with either R410A or R454B data and then attempt to predict the performance of the other refrigerant.

The results, depicted in Figures 5, showcase the compressor power consumption, and discharge temperature predictions. In these Figures, the predicted data are plotted on the vertical axes as a function of actual values. It is important to note that Figures 5 and 6 are plotted for the case in which proposed model is trained with refrigerant R410A training data set of rotary compressor and then tested with testing data set of the same rotary compressor with R454B refrigerant. Even with refrigerant sensitivity analysis, the power prediction is under 2% MAPE while the discharge temperature shows almost 4K MAE.

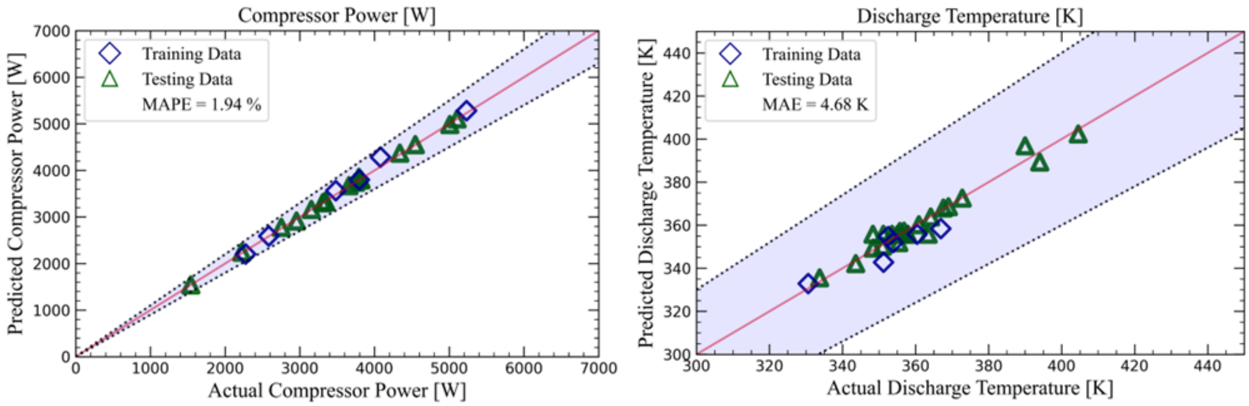

Figure 5: ANN Results for refrigerant sensitivity analysis of Compressor Power (left) and Discharge Temperature (right)

Figure 6 illustrates the parity plots of the evaporator and injection mass flow rate predicted by ANN for refrigerant sensitivity analysis plotted on the vertical axes against the actual values on the horizontal axes, respectively. Based on the results, the outcomes of ANN are linearly aligned, confirming the suitability of the proposed ANN model for the prediction of evaporation and injection mass flow rate. The MAPE in both the cases of evaporator and injection mass flow rate is less than 5%.

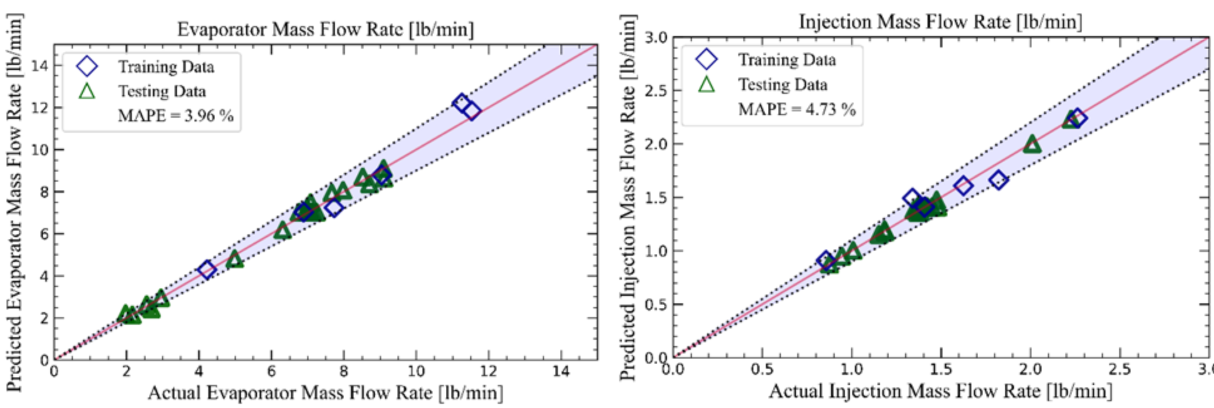

Figure 6: ANN results for refrigerant sensitivity analysis for Evaporator (left) and Injection Mass Flow Rate (right)

The results are summarized in Table 4, which shows the MAPE values range from 2-3% for compressor power and mass flow rates, whereas for discharge temperature, the MAE values typically fall within the range of 3-4 K, with a few exceptions exceeding these boundaries. In addition to the robust predictive capabilities of ANN, it is imperative to highlight the criticality of selecting appropriate hyperparameters such as the number of nodes, hidden layers, activation function, and solver, particularly in complex systems like compressors. Improper choices in these hyperparameters may lead to overfitting, resulting in inaccurate predictions.

Table 4: Summary of ANN model results for refrigerant sensitivity analysis

Datasets		$\dot{W}_{comp}$	$\dot{m}_{evap}$	$\dot{m}_{inj}$	T_{dis}
Training Data	Testing Data	MAPE (%)	MAPE (%)	MAPE (%)	MAE (K)
Rotary R410A	Rotary R454B	1.941	3.946	4.731	4.681
Rotary R454B	Rotary R410A	0.798	3.251	1.922	3.451
Scroll R410A	Scroll R454B	2.124	3.542	2.547	3.825
Scroll R454B	Scroll R410A	2.548	2.981	3.154	4.254

5. CONCLUSION

Given the significance of vapor injection compressor performance in air source heat pumps and the limitations observed in existing models within this research domain, this study leveraged an Artificial Neural Network (ANN) model to predict the output parameters of vapor injection compressors operating with R410A, R454B, and R407C. A datasets comprising 195 data points sourced from both in-house experiments and literature was employed to develop the proposed ANN model. Key parameters such as compressor rotational speed, suction, injection, and discharge pressures, were utilized as inputs to the model, while compressor power, injection, and evaporator mass flow rates and compressor discharge temperature served as outputs.

To evaluate the reliability of the proposed ANN model, two statistical error metrics were employed, and the results were extensively discussed. The findings indicated that the ANN model exhibited a high level of accuracy and efficiency in predicting the output parameters of vapor-injected compressors. However, it was noted that the accuracy of the ANN model was contingent upon the quality and quantity of the training dataset. In the case of refrigerant sensitivity, the MAPE was less than 5% for all output parameters. Overall, the suggested model is faster and displays better performance as well as simpler to use and reliable, which can be great addition to the modeling side of HVAC factories for predicting vapor injected compressors performance for system development by integrating the proposed model with system model. Future attempts should be practiced optimizing the activation functions, number of neurons per layer, and training algorithm for better ANN structure for a specific problem.

NOMENCLATURE

$\dot{m}_{inj}$	Mass flow rate through the injection line	[kg/s]
$\dot{m}_{evap}$	Mass flow rate through evaporator	[kg/s]
p_{cond}	Condensing pressure	[kPa]
p_{inj}	Injection pressure	[kPa]
p_{evap}	Evaporating pressure	[kPa]
T_{dis}	Discharge temperature	[°C]
$\dot{W}_{comp}$	Compressor power	[kW]

Abbreviations

ANN	Artificial Neural Network
AHRI	Air-Conditioning, Heating, and Refrigeration Institute
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error

Greek Symbols

ω	Compressor speed	[rpm]

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