Evaluation And Quantification Of Semi-Empirical Compressor Model Predictive Capabilities Under Modulation And Extrapolation Scenarios

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ABSTRACT

Testing and evaluation of select semi-empirical compressor models is carried out to quantify performance in modulation and extrapolation scenarios. Three representative models from literature are benchmarked against an artificial neural network (ANN) model and the industry standard AHRI model. A methodology for quantifying model performance, compared against experimental data, in extrapolation and modulation scenarios is presented. Predictions from the five models are compared against high-fidelity performance data taken from either a hot-gas bypass load stand or a compressor calorimeter. Scroll, screw, reciprocating, and spool compressor technologies were collected with R410A, R1234ze(E), R134a, and R32 refrigerants. In total, 327 experimental data points were used for model testing. The Mean Absolute Percentage Error (MAPE) is calculated for the mass flow rate and power of each compressor providing a means to quantify the model's ability to predict experimental data under modulation and extrapolation scenarios. The semi-empirical models yield MAPE's less than 5% for mass flow rate and power in modulation scenarios while performing at or below 8% MAPE in envelope extrapolation scenarios. The semi-empirical models capture superheat extrapolation to below 6% MAPE for mass flow rate and power with the exception of one model, the Popovic and Shapiro model performing at 18% MAPE in power prediction for Spool compressor working with R1234ze(E). The semi-empirical models show a maximum extrapolation MAPE of 7.3%, given the model captures the compressor technology. The empirical formulations do not predict modulation behavior and showed varying performance at the extrapolation scenarios, with the ANN performing the best. Future work based on the presented results include the development of a new model, based on a semi-empirical formulation that can capture multiple compressor technologies while exhibiting good modulation and extrapolation capabilities.

1. INTRODUCTION

Today compressor manufactures are challenged by regulatory changes aimed at mitigating climate change and global warming, while simultaneously meeting or exceeding system efficiency requirements. Modeling compressor performance plays a vital part in estimating overall system behavior and minimizing the energy footprint of these machines. All compressor models exist on a spectrum, ranging from black-box (statistical correlations) to white-box (distributed models). Black-box models require little information about the machine itself, while white-box models require detailed input information sometimes only known by the manufacturer. The most well known black-box model is the industry standard 10-coefficient map standardized by AHRI 540, AHRI (2020). Grey-box or semi-empirical models aim to hit the middle ground between the two extremes. These models are more computationally efficient than white-box models and can be implemented into system simulations but include additional fidelity that black-box models typically do not. This work aims to identify select semi-empirical compressor models from literature, quantify performance at extrapolation and modulation scenarios, and give insights to enhance a future model developed that is capable of predicting multiple compressor technologies in said scenarios.

Shao et al. (2004) presents a map based modeling approach for predicting mass flow rate, power, and COP at different supply frequencies for a rolling piston compressor. A mass flow rate and power ratio are defined which relate variable speed operation to that at a constant speed. This approach is adopted by Aprea and Renno (2008) to predict variable speed reciprocating compressor data. Another black-box style approach by Qiao et al. (2014) used pressure ratio and normalized speed to predict scroll compressor performance in a transient multi-evaporator system simulation. The model utilized curve fitted coefficients in expressions for volumetric efficiency, power, and discharge enthalpy. These models differ from semi-empirical methods that do use data to fit coefficients, but are reliant on tuned equations that closer resemble the physical phenomena occurring in the machine. Popovic and Shapiro (1995) present a method derived for reciprocating compressors based on a polytropic compression process and three control volumes. It predicts mass flow rate, power, and discharge temperature using 8 model inputs. Jahnig et al. (2000) and Mackensen et al. (2002) similarly employ a polytropic compression reference process model to predict reciprocating compressor performance. A formation presented by Winandy et al. (2002a) captures bulk phenomena occurring throughout the refrigerant evolution from suction to discharge stub of a scroll compressor. The model incorporates heat transfer acting on the suction and discharge gas flows, and heat transfer coefficients are fitted to data. The model represents the compression process in two steps; isentropic to the built in volume ratio then adiabatic and isochoric to the discharge pressure. This model has been adapted to capture reciprocating compressors Winandy et al. (2002b), rolling piston compressors Molinaroli et al. (2017), screw compressors Giuffrida (2016), liquid and vapor injected scroll compressors Winandy and Lebrun (2002), and oil flooded scroll compressors James et al. (2016).

Recently, machine learning based approaches have been used for compressor performance prediction in HVAC&R systems. Ziviani et al. (2018) studied ANN performance applied to positive displacement compressor and expanders. Ledesma et al. (2015) predicted reciprocating compressor performance using an ANN and proposed an iterative algorithm to change the number of neurons in the hidden layer until a leveling of the mean squared error (MSE) occurs, which sets the minimum number of neurons needed. Ma et al. (2020) proposed a compressor mapping methodology to inform training data selection used during the ANN development. Points were added to the training data based on which points exhibited the highest absolute percentage error (APE) between ANN prediction and experimental data. Wan et al. (2021) applied multiple machine learning techniques including convolution neural networks, deep neural networks, random forest, and support vector regression to predict mass flow rate and power for transient and steady state compressor performance. Other studies found in literature applying machine learning to HVAC&R compressor modeling include Sanaye et al. (2010) who predicted rotary vane compressor performance, Yang et al. (2009) predicted scroll, screw, and reciprocating performance, Barroso-Maldonado et al. (2017) predicted reciprocating compressor performance, and Zendehboudi et al. (2017) modeled variable speed scroll compressors with vapor injection.

1.1 Model Selection Criteria and Selected Models

It is infeasible to formally evaluate all the variants of compressor models presented here. Therefore a subset of models that encapsulate the general model types and modalities are selected. A model must meet basic performance criteria and successfully demonstrate modulation and extrapolation capabilities. The criteria includes limited training data, accuracy of 5% or better compared to experimental data, computational speed that is insignificant using modern computers, once trained, and requires as little proprietary knowledge about that compressor as possible. This criteria creates a basis for quantitative and qualitative preliminary selection of models, which resulted in five models selected.

The first model is used to baseline results as it is the industry standard approach for system modeling and presentation, AHRI (2020). The model has well documented limitations in both extrapolation and modulation scenarios, but will provide a basis of comparison. The second model is an Artificial Neural Network (ANN) which has recently shown promise as a black box alternative, Ziviani et al. (2019). The model proposed by Shao et al. (2004) is another black-box approach selected. This is due to its inclusion of modulation and high-accuracy. The model by Popovic and Shapiro (1995) is selected as a gray-box model, where a thermodynamic reference process is used and good accuracy achieved. Finally, the Winandy et al. (2002a) model is selected due to it's high accuracy and high-level of physical phenomena included. Neither Popovic and Shapiro (1995) or Winandy et al. (2002a) have been evaluated in the extrapolation and modulation modalities, but the increased physics fidelity made them promising candidates for this study.

2. SELECTED MODEL DESCRIPTIONS

This section provides a detailed technical description of each of the five compressor models selected for evaluation. This is split into a baseline model, the AHRI 10-coefficient map AHRI (2020), and four models or approaches from literature, the ANN approach, the Shao model, Shao et al. (2004), the Popovic and Shapiro model, Popovic and Shapiro (1995), and the Winandy model, Winandy et al. (2002a).

2.1 Baseline Model - AHRI Model

The AHRI model, described in AHRI (2020), is a mathemtically simple third order curve fit with 10 coefficients. While it can be reflected in many forms, most fundamentally, it provides functions for mass flow rate and power. The mass flow rate and power are fitted separately to evaporating and condensing temperatures resulting in two equations for performance prediction. The method is very accurate with respect to the data it is fitted to Aute et al. (2015). It is computationally efficient and requires almost no information about the compressor. It is used extensively in the

HVAC&R industry for system level modeling, therefore it is used as a baseline for comparison in the present study. In this formulation there are 20 tuning factors required for power and mass flow rate prediction and the needed inputs are suction and discharge dewpoint temperatures. This model requires no specific compressor information required in order to predict performance.

2.2 Models from Literature

2.2.1 Artificial Neural Network Model

The ANN modeling approach is black-box in nature and is composed of nodes and layers which take numerical inputs. The model requires data to inform an optimization algorithm which adjusts weights and biases within the network based on backpropagation of error determined by a loss function. The optimization algorithm and loss function used for this work were the Adam optimizer, Kingma and Ba (2015), and the MAPE. These yielded sufficient results during model development. The present study uses evaporating, condensing, and suction temperatures as inputs to the network while mass flow rate and power are outputs. Fully connected dense neural networks are implemented. Shallow neural networks are chosen for simplicity and reduced training time such that all models have one input layer, one hidden, and one output layer. To further reduce training time and keep input order of magnitudes similar, all inputs were normalized between 0.1 and 0.9, Ma et al. (2020). The rectified linear activation function, which sends negative input values to a node to zero and retains the value for positive inputs was chosen for this work. Model formulations are codified in the Python programming language. An open source machine learning package developed by Google, Tensorflow Abadi et al. (2016), is used to initialize, compile, fit, and evaluate models. Data used for model development is split randomly as 80% training data and 20% validation data. To keep the model from overfitting the validation loss metric is monitored via callbacks during training and visually at the conclusion of a training run. Table 1 summarizes the neural network architecture utilized in this study.

Table 1: Artificial neural network characteristics for the present study

Parameter	Value
Machine Learning Package	Tensorflow 2.5.0
No. of Inputs	3
No. of Outputs	2
No. of Layers	1
No. of Nodes	8
Activation Function	Rectified Linear
Optimizer	Adam

2.2.2 The Shao Model

The Shao model from Shao et al. (2004) is a black-box model that utilizes performance data at different operational frequencies for fitting equation coefficients. The equations for mass flow rate and power are second order functions of evaporating and condensing temperatures. They need six coefficients tuned to data at nominal speed for both the mass flow rate and power formulations. The variable speed data is used to fit a second order function of frequency to the mass flow rate and power ratios. The ratios relate the mass flow or power at nominal nominal frequency to that at variable frequency.

In total, there are 18 coefficients needed to run the model. Each equation is fitted via least squares. The model inputs are evaporating temperature, condensing temperature, and compressor frequency. There is no compressor specific information needed to run the model. However, with respect to training data, there must be at least three data points measured at variable speed operating conditions to fit the mass flow rate and power ratio equations.

2.2.3 The Popovic and Shapiro Model

The Popovic and Shapiro model from Popovic and Shapiro (1995) is a semi-empirical compressor derived to predict reciprocating compressor performance. The model utilizes an idealized polytropic compression and clearance volume re-expansion with constant pressure suction and discharge processes. This cycle is modified to include phenomena typical to a compressor. This includes utilizing volumetric volumetric efficiency, based on a clearance factor taken as an unknown. The authors then add suction and discharge pressure drop and, for simplicity, set the magnitudes equal. The model utilizes the thermodynamic work rate of a polytropic process as a basis for compressor power requirement. It splits the compressor into three control volumes, a compressor control volume, and two internal control volumes, the motor and the cylinder.

The heat transfer loss coefficient expression needs two coefficients tuned to data while the polytropic exponent expression needs three. The constant pressure drop term and clearance factor are fitted to data yielding 7 total parameters determined from data. Once these are known, four inputs are needed to run the model; refrigerant inlet state, outlet pressure, motor speed, and the piston displacement rate. It must be noted that training data for this model must include discharge temperature in order to fit the polytropic exponent expression.

2.2.4 The Winandy Model

The Winandy model, presented in Winandy et al. (2002a), is a gray-box semi-empirical model derived to predict scroll compressor performance. The model defines an isothermal wall which delivers heat to the suction gas, removes heat from the discharge gas, absorbs electro-mechanical losses, and exchanges heat with ambient. The compression process is broken into two steps, 1) isentropic compression up to the adapted pressure, then 2) adiabatic and isochoric compression to discharge pressure. The adapted pressure represents the pressure during isentropic compression up to the internal volume ratio of the scroll wraps. The mass flow rate is predicted by using a swept volume taken as an unknown in the formulation, the rotational speed, and the suction specific volume evaluated after the suction heat transfer process. All heat transfers to or from the isothermal wall require heat transfer coefficients which are tuned to data. The overall power prediction is the sum of a compression power term, a constant electro-mechanical loss term, and another electro-mechanical loss term which is proportional to the compression power.

The model needs seven parameters tuned to data. These include the suction, discharge, and ambient heat transfer coefficients (AU_{su}), (AU_{dis}), (AU_{amb}) respectively, the fictitious swept volume (V_s), the volume ratio (ε), a work loss term ($\dot{W}_{loss}$), and finally a work loss coefficient (α). There are seven model inputs to calculate mass flow rate and power once the parameters are tuned which are: suction and discharge pressure, suction temperature, a reference mass flow rate, ambient temperature, rotational speed, and refrigerant. The authors originally codified the model in Engineering Equation Solver (EES) and tuned the parameters manually, however the model used for this study was codified in Python using the Nedler-Mead optimization algorithm to minimize the mean absolute percentage error (MAPE) between model predicted mass flow rate and power and the data mass flow rate and power. There is no detailed information regarding the compressor needed to run the model.

3. HIGH FIDELITY DATA COLLECTION AND MODEL TESTING METHODOLOGY

High fidelity data collected compliant with ASHRAE standard 23.1 ASHRAE (2010) was used to train each of the five model presented and explore their behavior against three additional subsets focused on extrapolation, modulation (variable speed), and variable superheat behavior. Performance data for four compressor technologies; scroll, screw, reciprocating, and spool compressors are used with four working fluids, R134a, R410A, R1234ze(E), and R32. A total of 327 different data points were used. The compressor types, refrigerants, number of data points, collection standard, reference, and data splits are summarized in Table 2. Data splits are described in detail in the Section 3.2.

Table 2: Information on the data sets collected.

Compressor Type	Capacity	Refrigerant	Data Points	Collection Standard	Reference	Splits
Spool	40 tons	R-134a	58	ASHRAE 23.1	In House Data	4
Spool	40 tons	R-1234ze(E)	44	ASHRAE 23.1	In House Data	4
Scroll	2.5 tons	R-410A	196	ASHRAE 23.1	AREP #11	3
Twin screw	75 tons	R-134a	13	ASHRAE 23.1	In House Data	2
Reciprocating	2 tons	R-32	16	Not Mentioned	AREP #59	2

3.1 Data Collection Sources and Standards

Data sets came from measured data that was collected at Oklahoma State University's (OSU) 10-80 ton hot-gas bypass compressor load stand and from a 3 ton compressor calorimeter at the Heat Exchanger Advanced Testing Facility at Oak Ridge National Laboratory. The data collected at OSU is labelled 'In House Data'. The data collected at Oak Ridge was motivated by an initiative at AHRI called the Low-GWP Alternative Refrigerants Evaluation Program (AREP). Details of the data can be found in Table 2. Testing was conducted in accordance to ASHRAE Standard 23.1, ASHRAE (2010), except for AREP Report #59 which didn't report a collection standard.

3.2 Data Subsets (Splits)

Shown graphically in Figure 1, each data set was collected in bulk and had to be split into subsets (splits) for model capability testing. The full data set includes all variations, including various saturated suction temperatures, saturated discharge temperatures and variable superheat and/or speed/frequency. Each full data set collected is somewhat unique in its operating envelope and parameters varied, therefore the number of splits is unique. For example, the reciprocating data set did not include variable superheat or variable speed data. Hence, there are only two splits shown in Table 2, these are the training set and extrapolation set. The next sections will describe further the underlying principles of the decision making processes to make the splits.

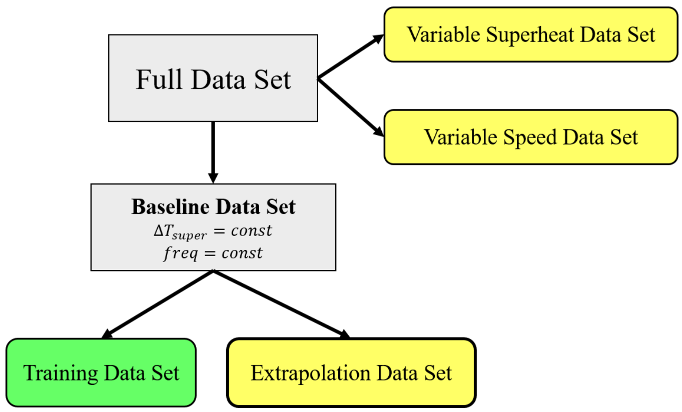

Figure 1: Flowchart showing how a data set was split into subsets for model evaluation

3.2.1 Baseline and Training Data Sets

Baseline data was split from the full data set to include various saturated suction/discharge temperatures at fixed superheat and compressor speed/frequency. Only the saturated suction/discharge temperatures vary in the baseline data set. From there, the baseline data is split into a training data set used to train model parameters and an extrapolation data set used to evaluate extrapolation capabilities. Ten data points were selected as the training data set to train the models. Motivation for this number of training points stems from the AHRI model requirements for ten data points to tune its ten regression coefficients. The training data set is selected at points interior to the most extreme envelope conditions (*i.e.* most extreme saturated suction and saturated discharge temperatures) present within a data set.

3.2.2 Extrapolation and Variable Speed/Superheat Data Sets

The extrapolation data set is a subset of the baseline data and includes saturated suction and discharge temperatures that extend beyond the envelope of the training data set. This varied based on compressor technology but extended the saturated suction and discharge temperatures by 10°C and 16°C, respectively, beyond the training envelope, at the most extreme.

The variable speed data set was only available for the spool and screw compressors. This data set has a fixed saturated suction and discharge temperature and superheat with variable operating speed/frequency. It includes speed variation ranging from 1036 - 1790 rpm for the spool compressor with 17 points and 4300 - 5700 rpm for the screw compressor with 7 points. The saturated suction/discharge and superheat for the compressors is 4 and 16 °C, and 11 K, 4 and 51 °C, and 5 K for the spool, and screw compressor, respectively.

The variable superheat data sets were only available for scroll and spool compressors. The spool data sets have 14 points with fixed speed of 1640 rpm at constant saturated suction and discharge temperatures of 5 and 37 °C with superheats that vary 8 to 27 K. Additionally, 13 points have; fixed suction temperature of 11 °C, saturated suction temperatures ranging from -11 to 10 °C, constant saturated discharge temperature of 37 °C, superheats that vary 8 - 40 K, and a fixed speed of 1640 rpm. Lastly, there are four miscellaneous points at 25 and 33 K superheat, -1 °C and 7 °C saturated suction temperature, respectively, a 51 °C saturated discharge temperature, and again a fixed speed at 1640 rpm. The scroll data set has 64 points at 22 K superheat spanning the entire operating envelope at a constant speed of 3600 rpm. It also included 66 points spanning the envelope at constant suction temperature of 18 °C, superheats spanning 5 - 30 K, and a fixed speed of 3600 rpm.

3.2.3 Model Testing Methodology

Figure 2 graphically describes the methodology utilized for this study. For each compressor technology, each of the five models are first trained using their accompanying training data set. Then the trained model is ran with and compared against experimental data from the other three data subsets. The model performance is evaluated using the trained models ability to predict the various subsets of experimental data evaluated using the Mean Absolute Percentage Error (MAPE),

$$MAPE_{\alpha} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{Y_{true,i} - Y_{predict,i}}{Y_{true,i}}\right| \tag{1}$$

where α represents the error for mass flow rate or power, n is the total number of data points in the data set, i is a specific data point, and $Y_{true,i}$ and $Y_{predict,i}$ are the measured data value and model predicted value, respectively, for mass flow rate or power at a given data point i.

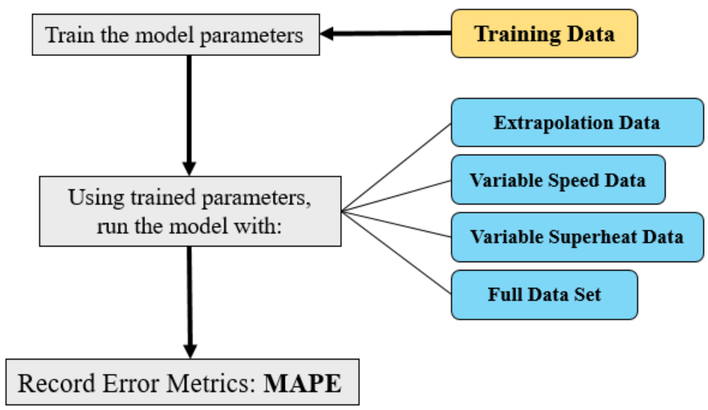

Figure 2: Flowchart showing how data sets were split into subsets for model evaluation

4. RESULTS

The five models were tested at modulation and extrapolation scenarios following the methodology outlined in Section 3.2.3 with results presented in this section showing the models ability to predict mass flow rate and compressor power. The screw compressor results are not in shown in Section 4.1 because less than ten points in the set were available to train the models. Six points in the screw data set qualified as training data and therefore those were used to train the models. The AHRI model, requiring a minimum of ten points, could not be evaluated with the screw data available. Therefore, those MAPE values are not shown in Figure 3. The models which could be trained with the data yielded results shown in Table 3.

4.1 Training Data

Figure 3 gives two bar charts showing model performances at the training conditions for each data set. The Winandy model does not predict reciprocating compressor performance as shown by MAPEs greater than 15%. The model was derived for scroll compressors and performed under 5% MAPE for power and mass flow rate prediction when applied to spool, screw, and scroll compressor data. The Popovic and Shapiro model did not predict scroll compressor data showing MAPEs above 15%. The model was derived to predict reciprocating compressors, where it performed under 7% MAPE. The black-box models performed well showing a largest MAPE of 6.3% for the ANN at mass flow prediction for screw compressor data. These models showed MAPEs below 1% in 16 out of the 28 cases recorded with the AHRI model performing best overall at training data prediction. Table 3 shows MAPE values achieved for all models in numerical format. The mass flow rate error followed by the power error in parenthesis is given for every combination of model and compressor data. Excluding cases where a model didn't predict a certain compressor technology, the largest MAPE was 6.8 and 6.1 % for mass flow rate and power, respectively, coming from the Popovic and Shapiro model.

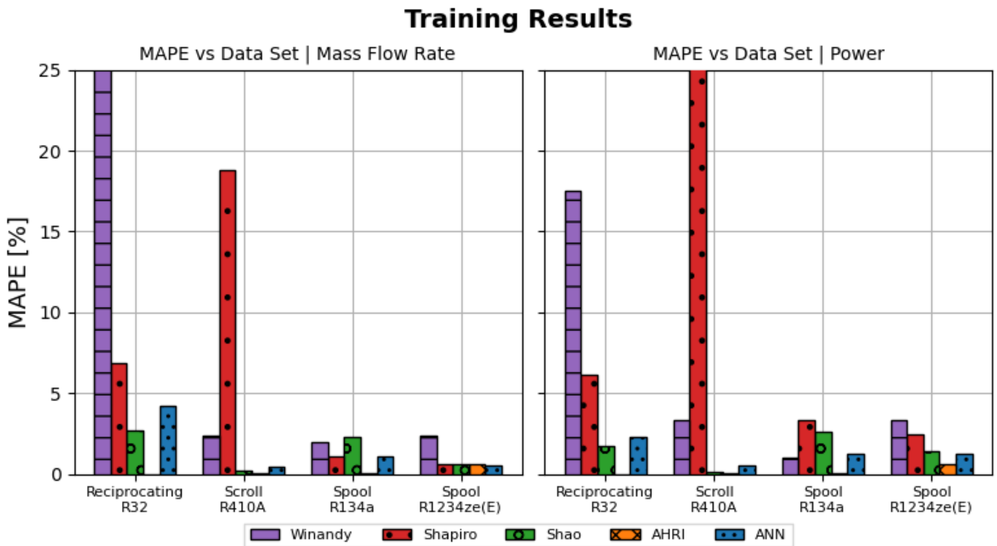

Figure 3: Training results at each data set for the five models

Table 3: Model MAPE results for training data sets

	Model MAPE: Mass Flow Rate, (Power)									
Data Set	Winandy		Popovic & Shapiro		Shao		AHRI		ANN	
Recip. R32	26.5%	(17.3%)	6.8%	(6.1%)	2.7%	(1.7%)	1e-3%	(2e-3%)	4.3%	(2.3%)
Scroll R410A	2.4%	(3.4%)	18.8%	(159%)	0.2%	(0.1%)	6e-2%	(3e-2%)	0.4%	(0.5%)
Spool R134a	2.0%	(1.0%)	1.1%	(3.3%)	2.3%	(2.6%)	6e-2%	(4e-2%)	1.1%	(1.3%)
Spool ze(E)	2.4%	(3.4%)	0.6%	(2.4%)	0.6%	(1.4%)	4e-2%	(0.6%)	0.5%	(1.2%)
Screw R134a	1.2%	(0.6%)	0.2%	(0.2%)	0.1%	(0.4%)	n/a	(n/a)	6.3%	(4.1%)

4.2 Modulation

Figure 4 represents the MAPEs of model predicted results for each of the models using the three modulation data sets described in Section 3.2.2. In Figure 4, the results show the Winandy, Popovic and Shapiro, and the Shao model capture mass flow rate at MAPE's less than 5%. This provides good indication that the aforementioned models could be used to predict mass flow rate at conditions outside that of their training data. The ANN model produced mass flow rate errors around 20%. The errors achieved for the AHRI model are not shown on Figure 4 because, as mentioned in Section 4 the screw compressor data did have ten data points at constant superheat and speed to train the model's coefficients. The errors achieved for spool compressor mass flow rate using R134a and R1234ze(E) when running the AHRI model were 20.7% and 20.3%, respectively, as shown in Table 4.

Table 4: Model MAPE results for modulation (variable speed) data sets

	Model MAPE: Mass Flow Rate, (Power)									
Data Set	Winandy		Popovic & Shapiro		Shao		AHRI		ANN	
Spool R134a	3.1%	(2.0%)	2.3%	(4.5%)	3.6%	(2.5%)	20.7%	(20.2%)	19.9%	(19.1%)
Spool ze(E)	3.1%	(3.0%)	2.2%	(2.4%)	2.9%	(2.6%)	20.3%	(21.4%)	19.6%	(20.4%)
Screw R134a	1.7%	(0.7%)	1.1%	(0.4%)	0.8%	(2.6%)	n/a	(n/a)	25.2%	(20.6%)

For power prediction, Figure 4 shows MAPE values were similar to MAPEs achieved for mass flow rate for all models. The Winandy, Popovic and Shapiro, and Shao model performed under 5% MAPE. The ANN model performs at MAPE's around 20% for power prediction when tested at modulation scenarios. The errors tabulated in 4 show the

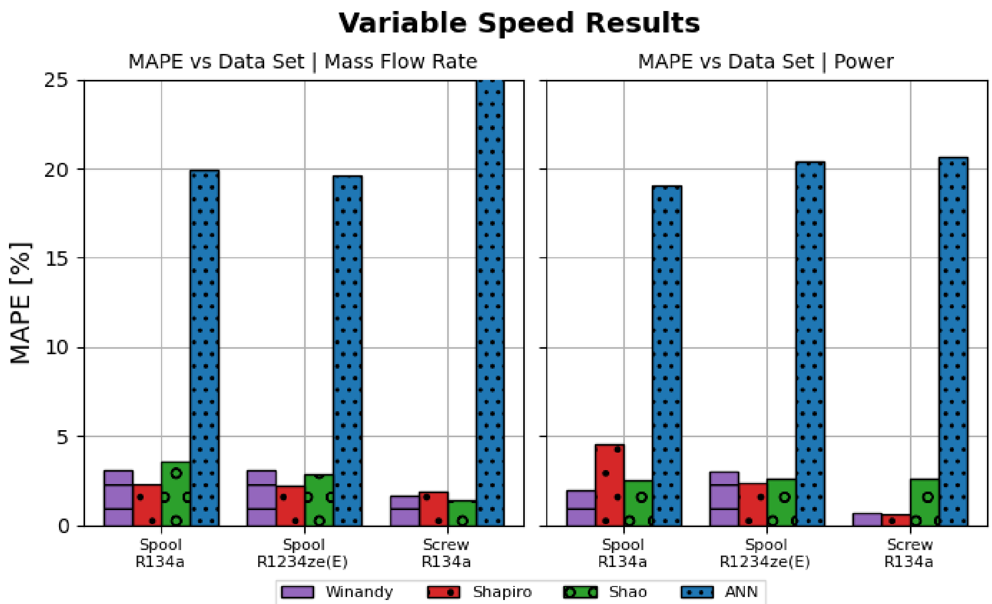

Figure 4: Mass flow rate and power results under modulation (variable speed) testing

AHRI and ANN models in their present form are not adequate to predict modulation performance for compressors. During training of the ANN, points at variable speed conditions could be included to improve prediction, however the present work studied performance at precise training conditions to examine capabilities and record performance at conditions different to that of the training data.

4.3 Extrapolation

Figure 5 represents the MAPEs of model predicted results for each of the models using the extrapolation data sets described in Section 3.2.2 with results summarized in Table 5. Shown in Figure 5, extrapolation is captured by the semi-empirical models, given that they do predict the compressor technology. The Winandy model performs below 6% for the scroll and spool compressor technologies. The model extrapolated with two different refrigerant data sets for the spool compressor. The model did not capture reciprocating compressor performance. The Popovic and Shapiro model extrapolated below 8% MAPE for the compressor technologies that it predicted. This model however, did not capture scroll compressor technology but performed better at extrapolating spool compressor data than reciprocating data, the latter of which the model was derived initially to predict. The ANN model extrapolated below 3% except in the case of power prediction for the spool compressor utilizing R134a and mass flow rate prediction for the reciprocating compressor using R32. The Shao model performed well when ran with scroll and the spool R1234ze(E) data, however extrapolation errors rose to 8.2% and 10.7% for the reciprocating and spool R134a data respectively. The AHRI model did not perform adequately when extrapolating as can be seen by the errors rising from 45.% to 7.0e+6.

Table 5: Model MAPE results under extrapolation scenarios

	Model MAPE: Mass Flow Rate, (Power)									
Data Set	Winandy		Popovic & Shapiro		Shao		AHRI		ANN	
Recip. R32	23.3%	(16.4%)	7.3%	(6.6%)	10.7%	(8.6%)	45.1%	(27.5%)	2.9%	(8.5%)
Scroll R410A	3.6%	(3.1%)	19.3%	(3e3%)	1.5%	(0.4%)	6e5%	(9e5%)	1.4%	(0.8%)
Spool R134a	5.7%	(2.7%)	3.6%	(3.9%)	8.2%	(6.8%)	6e6%	(7e6%)	11.9%	(1.9%)
Spool ze(E)	3.0%	(2.3%)	1.2%	(5.8%)	2.6%	(2.6%)	4e6%	(6e4%)	1.3%	(1.9%)

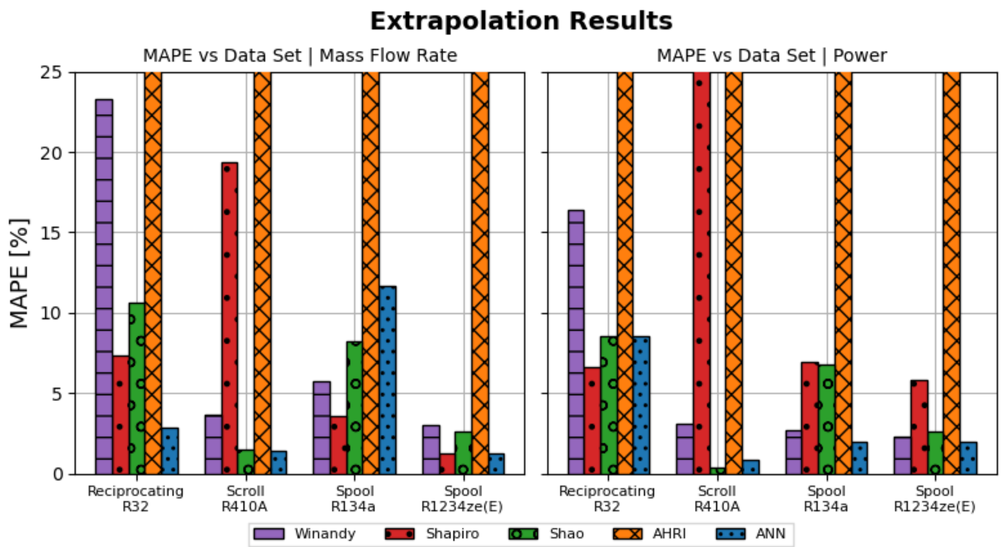

Figure 5: MAPE results at extrapolation conditions

5. CONCLUSIONS

The present work studied the extrapolation and modulation capabilities of select semi-empirical compressor models. Data sets selected for model testing were of high fidelity to ensure model prediction is accurate to measured data instead of manufacture published data. Data sets were split to enable training model parameters at constant conditions then test model with data outside that of the training data. Four different data sets were identified and used: the training data set, extrapolation data set and variable speed data set. Models were trained using the training data set then tested at the others to record performance. Based on the results, the semi-empirical models outperform the empirical models when considering all aspects desired by the author. These were: limited training data, low computational cost, and accurate performance at extrapolation and modulation scenarios. Given that the model predicted the compressor technology, the highest MAPE for mass flow rate came from the Popovic and Shapiro model at 7.3%. For power prediction the same model recorded the highest error, which was 6.9%. The more empirical Shao model gave promising results for mass flow rate and power prediction in modulation scenarios, however, mixed results were achieved in extrapolation testing where resulting MAPE's ranged from 0.4% to 42.2%. The AHRI formulation performed the worst in modulation and extrapolation scenarios. Results show that the model should not be used in modulation scenarios or beyond the bounds of its' training data. The ANN model has performed poorly in modulation scenarios where errors above 19% were recorded in all data sets. In extrapolation scenarios, results were mixed with MAPE's between 0.8% and 25.5%.From these results conclusions can be made regarding the performance of semi-empirical and empirical models.

- The Winandy model, as tested, will capture extrapolation and modulation in scroll, screw, and spool compressors
- The ANN model cannot predict performance during compressor modulation, given a constant speed training data set
- The Shao model, even though empirical in nature, will capture modulation scenarios
- The AHRI model will not predict compressor performance under modulation or extrapolation scenarios
- Given the Winandy model predicts the compressor technology, this model outperformed the others tested in this study

The model proposed by Winandy et al. (2002a) is chosen as a formulation with promising attributes for future model development. As cited in the literature survey, this formulation has been modified to capture a range of technologies and will be the basis for a new model desired to capture multiple compressor technologies and exhibit strong extrapolation and modulation capabilities.

NOMENCLATURE

MAPE	Mean Absolute Percentage Error	(%)
ΔT_{super}	Suction gas superheat	(K)
freq	Compressor rotational frequency	(Hz)
α	In Eq. 1, represents either power or mass flow rate	
n	Total number of data points	
i	Individual data point	
Y_{true}	Measured value	
$Y_{predict}$	Modeled value	

Compressor Data Sets

Scroll 1	Scroll R410 compressor data set containing points with superheat values of 22 K
Scroll 2	Scroll R410 compressor data set containing constant suction temperature data points, at 18°C

Shorthand

ANN	Artificial Neural Network
ze(E)	Refrigerant R1234ze(E)
const.	Constant

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