Vapor Injection Compressors: A Review of Opportunities, Testing and Sampling Techniques, and Methods of Characterization

Timothy KIM[1]*, Dennis NASUTA[1], Shankhinee DESHPANDE[1], Song LI[1], Cara MARTIN[1]

[1]OTS R&D Inc., Beltsville, MD, USA
(tkim@ost-rd.com)

* Corresponding Author

ABSTRACT

In the race to fight climate change and live sustainably, heat pumps are becoming increasingly popular due to their ability to efficiently deliver heat using electricity. However, heat pump performance degrades at low ambient conditions, making implementation challenging in very cold climates. The introduction of vapor injection (VI) has been seen in experimental research to improve capacity and coefficient of performance (COP), especially at low ambient conditions with heat pumps. While the performance of such compressors is heavily researched, the industry still has no standardized practices for characterizing their performance. Currently, there are standard practices for testing VI compressors according to ASHRAE 23 and EN 13771 but rating standards do not provide specific guidance on the selection of test points and the fitting of data. Empirical models, such as AHRI Standard 540's 10-coefficient model, exist for fitting the data of non-VI compressors, but there is no equivalent model established for VI compressors. In order to incorporate the effects of additional varying parameters such as injection pressure, compressor frequency, superheat, and ambient temperature, new techniques for sampling and fitting data will be necessary since a fully empirical polynomial approach would require far too many tests and variables. This paper reviews the current practices/methods for compressor test sampling and performance mapping in academia for both VI and non-VI compressors. Accurate and reliable compressor performance mapping for VI will be important for the design and implementation of such compressors in HVAC equipment in the coming years. The authors are engaged in a multi-year research program funded by the Department of Energy and future work will include the construction of a compressor test stand that will be used to evaluate best practices for testing and characterizing VI compressor performance.

1. INTRODUCTION

Manufacturers have growing interest in the realm of vapor injection (VI) as the benefits from this technology are becoming clear from literature. Climate change has pushed heat pumps to be designed for colder and colder temperatures. This is where the addition of VI shines in its ability to boost the performance of such heat pumps. With conventional compressors, manufacturers follow AHRI Standard 540 (and/or similar international standards) to test compressors and produce coefficients for a standard 10-coefficient polynomial that estimates power and flow rate (and current and capacity) as functions of saturated suction and discharge temperatures. This model is fully empirical meaning the fitted coefficients and the form of equations (full third order polynomial with interactions) have no physical basis; it can produce errors in excess of 10% within the tested domain (Aute *et al.*, 2015), but can result in much greater errors when extrapolating beyond. Currently, no industry standard exists for vapor injected compressors, which is a critical barrier to the design and implementation of such compressors in systems.

A model for VI compressors must include injection pressure as an independent variable but should also ideally consider additional variables including compressor frequency, superheat, and ambient temperature, all of which influence performance but are overlooked by the current method. If the current methodology were extended, the inclusion of these additional parameters would result in hundreds of coefficients and test points, making it practically infeasible. The desired solution should have high accuracy while minimizing the testing burden and incorporating additional independent variables including injection pressure, frequency, superheat, and ambient temperature. The ability to accurately extrapolate performance beyond the test domain and apply it to multiple refrigerants is also highly valuable to heat pump designers. This paper examines methods for sampling and mapping compressor performance for both VI and non-VI compressors in the search for a preferred method to meet industry needs.

2. SAMPLING METHODS

Development of models that accurately predict performance requires collection of experimental observations across the full domain of operating conditions. While AHRI Standard 540 provides a polynomial format for fitting data, it sets no requirements for the number and distribution of test points. Aute *et al.* (2015) surveyed six manufacturers and found that most used 14 or more test points, which were shown to produce accurate maps relative to comprehensive datasets with over 600 test points. OTS conducted a similar survey in 2024 and found again that most manufacturers were collecting sufficient test data, but like Aute, learned that a small minority collected less than 10 test points per compressor, which could potentially lead to overfitting errors with a 10-coefficient model. Furthermore, manufacturers testing variable-speed VI compressors reported requiring 108-260 test points.

The design of experiments (DOE) plays a key role in determining the accuracy of a model and minimizing testing burden. Uniform grid-based sampling and traditional DOE methods such as Box-Behnken design, central composite design, and full- and fractional-factorial design are commonly used by industry, but they can still require a large testing burden and cannot be easily applied to non-rectangular domains. For example, a factorial design requiring three points per parameter would still require 3^4=81 tests when including suction, discharge, injection pressure as well as frequency. Adding superheat/suction density and ambient temperature would require an extremely burdensome 729 tests.

Aute *et al.* (2015) established the "polynomial design of experiments" (PDOE) method using clustering algorithms to identify uniformly distributed test points within the non-rectangular design space of a compressor envelope. Christ *et al.* (2023) extended this work with the scaling polytope design of experiments (SP-DOE) as a similar method for identifying test points in a non-rectangular design space using clustering. Marchante-Avellaneda *et al.* (2023) used D-optimal designs to demonstrate that accurate predictions could be made with less samples and correlations with less terms: as few as 6 test points were needed for a correlation with only 4 terms to achieve comparable accuracy. Lee *et al.* (2022) improved mass flow rate (MFR) prediction using a "two-point prediction method". Aute *et al.* (2015) states "for most compressors, the high errors occur in the region of the envelope with low suction and low discharge dew point temperatures." Lee's approach separates the model into two regions, therefore, reducing the error caused by extreme temperature differences in the envelope. By assigning reference points to predict condensing temperatures between 25 to 45 °C and 50 to 60 °C, Lee was able to improve MFR prediction from 34% within 5% error to 57% within 5% error.

While thoughtful DOE has been clearly demonstrated to improve model predictions and/or minimize compressor testing burden, it should also be clear that the form of the equations plays an even more critical role. The AHRI 10-coefficient polynomial has been successful in accurately predicting fixed-speed non-VI performance, however this method cannot be practically expanded to incorporate more variables. Cambio (2016) extended the logic of the 10-coefficient model to include injection pressure using 23-coefficients. This approach would obviously be impractical when adding frequency, superheat, and ambient temperature to create 262 terms. It is therefore necessary to look to different formulations when seeking to expand the capabilities of compressor maps to meet industry needs.

3. NON-VI MAPS

AHRI 540's 10-coefficient polynomial has been the standard for modeling fixed speed, non-VI compressors. This is a simple, empirical-based model that is reasonably accurate. Aute *et al.* (2015) conducted an analysis comparing this model with four other proposed models taken from the literature which showed that these models did not improve on the 10-coefficient model in general. While the generally robust 10-coefficient model has not significantly outperformed other physics-based and empirical models when fitted to sufficient test data, it does not account for ambient temperature or superheat, which is a major limitation. Aiding a model with physics-informed parameters should help to reduce the amount of tests required to model a compressor and may even extend the amount of refrigerants and compressors that one model can predict. In this sense, semi-empirical models may have the best advantages to achieve this. The landscape of written literature in this topic further supports this concept. A summary of the performance of such models can be found in Table 1.

Dabiri and Rice (1981) explored the effects of superheat on MFR using simple correction factor relations on existing manufacturing maps for previously studied compressors. Power was corrected on the isentropic efficiency assuming it does not depend on superheat. Oil fraction and ambient temperature were also identified as parameters affecting compressor performance where the author concludes ambient temperature may still have a factor in the differences between their superheat corrected model and the experimental data. Averaging amongst the four datasets, the MFR deviates by 4.9% from the experimental data compared to the corrected model, which is an improvement over the original maps deviation of 7.1%. However, in terms of power, the corrected model deviates 5.3% versus 4.7% for the original model. Aute *et al.* (2015) also compared the effect of superheat from the same four datasets comparing the MFR and power of the AHRI model against the physics-based models. They found 6% error for mass flow predictions on the AHRI model while the physics-based models had 3% error. This makes sense considering the physics-based models account for suction density which is affected by superheat. Surprisingly, the 10-coefficient model did better in predicting power for different superheat cases than the physics-based models. In both cases (Aute *et al.*, 2015; Dabiri and Rice, 1981), the new models were able to improve MFR predictions but performed worse for power.

Marchante-Avellaneda *et al.* (2023) explored the use of an empirical model with less terms than the AHRI model. They found that correlations with as little as three terms can produce very good results in predicting MFR and power. Overall, the correlation with six terms using the temperature "domain" (correlation 3) proved to have the best accuracy for mass flow while the correlation with six terms using the pressure "domain" (correlation 2) had the best accuracy for power prediction. While correlation 3 had the best result for mass flow prediction, the authors recommend using correlation 2 as it has the best compromise between experimental cost and accuracy for mass flow and power. Additionally, the authors show that use of pressure domain variables provide a more linear relation to the mass flow and power, which the authors allude may be used more universally with other refrigerants. Interestingly, the authors state that superheat does have a significant effect on compressor and volumetric efficiencies over a wide range of operating conditions but does not affect the power consumption. This conclusion is supported by Aute *et al.* (2015) and Dabiri and Rice (1981) and may suggest that power consumption is offset by some other mechanism (possibly lower MFR) even though it is seen to affect compressor efficiency, which in turn, should intuitively affect the power. Regression analysis from Marchante-Avellaneda *et al.* (2023) showed statistical significance for all coefficients of their correlations.

Winandy *et al.* (2022) developed a physics-based compressor model that predicted MFR and discharge temperature based on the swept volume and local heat transfer coefficients surrounding the compressor. Compressor power is also modeled based on the compressor volume ratio, a compressor power loss term and the power coefficient. This resulted in a good fit to the experimental data, having maximum percent errors of 3.5% for mass flow, 3% for power and maximum absolute error of 5K for the discharge temperature. However, this requires intimate knowledge of the compressor geometry, which will be undesirable for compressor manufacturers as such data may be deemed proprietary information.

A more exciting type of modeling that has seldom been researched is the use of artificial neural networks (ANN) to obtain models for compressors. The recent explosion of the use of AI has become more and more relevant in many applications and as the technology to train AI has gotten better, its potential for modeling compressors cannot be ignored. Ma *et al.* (2020) has explored the use of such machine learning techniques in three different compressors types (refer to Table 1). They were able to achieve slightly better predictions with the ANN with one less sample training the model against the 10-coefficient model using 11 samples. Belman-Flores *et al.* (2015) were able to achieve under 1% mean percent error (MPE) for mass flow, power and discharge temperature relative to the experimental data. In comparison, the physics-based model had mass flow, power and discharge temperature MPE of 7%, 7.5% and 0.18% respectively. While the author used 80% of the total data for training the model, which is a cause for concern of overfitting the data, the number of hidden layers was optimized to prevent overfitting.

Hjortland and Crawford (2024) performed a study of their own semi-empirical model with a massive dataset of 26 refrigerant/compressor combinations. This was compared directly to the 10-coefficient model which performed better than the proposed model when all data was used to obtain the model for predicting mass flow and power. However, when fewer training points were used, the 10-coefficient model performed worse. For discharge temperature, the proposed model proved to be superior regardless of the number of training samples. The model is elegant in its simplicity, using only 2-4 fitted coefficients for each of the predicted values, but maintaining fidelity due to its use of physical quantities like density, pressure, and temperature.

Table 1: Non-Vapor Injection Literature

Author	Refrigerant / Compressor	Model Type	Details	Error
Belman-Flores *et al.*, 2015	R1234yf, R134A / Reciprocating	Physics and Empirical	-ANN -Dataset for each refrigerant*	0.8% MFR MPE 0.8% Power MPE 0.08% Discharge MPE
Byrne *et al.*, 2014	R407C / Scroll	Semi-empirical	-Modified for R290, R1270 and R600A	10% MFR MaxPE 10% Power MaxPE 5K Discharge MaxAE
Cuevas and Lebrun, 2009	R134A / Scroll	Semi-empirical	-Variable speed	3 g/s MFR MaxAE -24 W power MaxAE -0.5K Discharge MaxAE
Dabiri and Rice, 1981	R22 / Reciprocating	Empirical	-Accounting for Suction SH -4 datasets*	4.9% MFR MPE 5.3% Power MPE
Guo *et al.*, 2017	R410A / Scroll	Empirical	-Variable speed	20% Power MaxPE
Hjortland and Crawford, 2024	Variable refrigerants / Mostly Scroll	Semi-empirical	-Use 14 data points vs all available -26 datasets*	1.3% MFR MAPE 1.4% Power MAPE 3.5 K Discharge MAE
Jahnig *et al.*, 2000	R134A or R12 / Reciprocating	Semi-empirical	-Consider effect of ambient temp -21 datasets*	2.9% MFR MaxPE 1.9% Power MaxPE
Lee *et al.*, 2021	R32, D2Y-60, L-41A / Scroll	Empirical	-Factor in SH	0.9% MFR MPE 0.3% Power MPE
Lee *et al.*, 2022	R410A / Rolling Piston	Semi-empirical	-2-point prediction	10% MFR MaxPE
Lee and Lam, 2013	R22, R134A, R407A, R410A / Scroll	Semi-empirical		1.5% MFR MPE 8.9% Power MPE
Li, 2012	R12, R134A, R22, R410A / Scroll or Reciprocating	Semi-empirical	-5% MFR -8% power -8 datasets* -Max relative extrapolate	3.2% MFR MaxPE 1.9% Power MaxPE 2.7K Discharge MaxAE
Ma *et al.*, 2020	R410A / Scroll, Reciprocating, Rolling piston	Empirical	-ANN -3 datasets*	1.9% MFR MAPE 2.2% Power MAPE
Mackensen *et al.*, 2002	R134A, R22, R717, R22 / Scroll, Recip., Screw, Rotary	Semi-empirical	-25 datasets*	1.8% MFR MAMWE 6.8% power MAMWE
Marchante-Avellaneda *et al.*, 2023	R134A, R32, R410A, R404A / Scroll	Empirical	-Correlation 3 best for MFR -Correlation 2 best for power -10 datasets*	1.3% MFR MaxPE 1.9% power MaxPE
Navarro-Peris *et al.*, 2013	R290, R407C / Scroll, Reciprocating	Semi-empirical	-Scroll model performed worse -4 datasets*	<5% MFR and power MaxPE
Ossorio and Navarro-Peris, 2023	R290, R410A, R134A / Scroll	Semi-empirical	-Variable speed -3 datasets*	8.7% Power loss MaxPE
Winandy *et al.*, 2002	R22 / Scroll	Physics		3.5% MFR MaxPE 3% Power MaxPE 5K Discharge MaxAE

*Absolute average taken for errors across datasets where multiple are available

Jahnig *et al.* (2000) also compares a proposed 5-parameter semi-empirical model against the 10-coefficient model with 21 combined datasets. Surface level inspection shows the 10-coefficient model outperforms the proposed model, but deeper analysis reveals this is due to the lack of datapoints available to perform an error analysis. On the flip side, the new model stayed relatively consistent with its errors regardless of the number of available data points. Marchante-Avellaneda *et al.* (2023) assessed the compromise between experimental cost and accuracy, therefore, looking at the accuracy per available sample might also provide valuable insight into the value per cost of a model as a standardized metric or the training sample normalized model accuracy (TSNMA). Accounting for the number of samples has a real-world impact on the resources spent to obtain a model. To do this, we can assume the minimum required samples for each model; 10 for 10-coefficient model and 4 for the 5-parameter model (mass flow and power model have 2 and 3 parameters respectively)). Therefore, the average model accuracy per sample of training data for mass flow and power are 9.6 %/sample and 9.9 %/sample, respectively for the AHRI model. Conversely, for the 5-parameter model, the accuracy per sample of training data for mass flow and power are 24.2 %/sample and 24.5% %/sample, respectively. The higher the number, the better, which indicates more accuracy value per sample trained. Here, it shows the proposed model can give you better accuracy with fewer trained samples.

Jahnig *et al.* (2000) also plots the curve fit of the AHRI model which clearly shows why it is bad at extrapolating performance. The nature of the polynomial causes it to skew wildly outside the fitted data which simply does not make physical sense. The author also tests the model with data that contained different ambient temperatures. They expected slightly lower MFR due to lower suction densities and little change to power due to lower MFR being offset by higher work increase. Results show little change to MFR with respect to ambient temperature and large underpredicted errors in power with respect to ambient temperature. Li (2012) was able to show extrapolation capabilities with their semi-empirical model, which showed comparable errors to the fitted data. Li (2012) also tested their model at different ambient temperatures using data provided by Jahnig *et al.* (2000) and found similar MFR and power.

Lee *et al.* (2021) tests their empirical model at various ambient temperatures. In their approach, results at lower ambient temperatures underpredicted power and MFR by as much as 11% and 62.5%, respectively for the original AHRI model. This improved to 0.7% and 0.4% for power and mass flow respectively with the new corrected map. Lee *et al.* (2021) explains the cause is because of the higher pressure ratios, which in turn, cause lower volumetric efficiencies. Lower volumetric efficiencies with respect to ambient temperature may explain the underprediction of power in the Jahnig *et al.* (2000) and Li (2012) model.

Ossorio and Navarro-Peris (2023) and Cuevas and Lebrun (2009) comment on the effect of variable frequency on the compressor model. Compressor efficiency is diminished at low frequencies, which is explained by the lack of lubrication that leads to leakages. Guo *et al.* (2017) also performs a correlation analysis showing high correlation between compressor frequency and power.

Review of literature here has shown that the AHRI model has significant limitations that can be improved upon. If an empirical model is to be used, it could be improved over the AHRI model with less terms using pressure domain. Additionally, many semi-empirical models were developed and showed these models can be better than the AHRI model with less training samples and/or improved ability to extrapolate or apply to different refrigerants. A new metric is also proposed to compare accuracy per training sample for the Jahnig *et al.* (2000) model.

4. VI MAPS

Although VI compressors have been utilized in refrigeration systems for many years now, their adoption into consumer and commercial heat pump products is relatively recent. As such, the capabilities of the conventional 10-coefficient model have not met the greater demands for a compressor model that can accurately predict VI performance to support present engineering design work. A summary of relevant studies is listed in Table 2 with highlights noted below. While the lessons learned from non-VI modeling assessments can be applied and expanded for VI technology, VI introduces significantly more complexity that must be considered.

Winandy and Lebrun (2002) developed a model that works for both vapor and liquid injection. This physics-based model accounts for the heat added and taken away from the refrigerant entering and exiting the compressor from the heat generated by the compressor itself and the ambient, signified by the “fictitious thermal wall”. Among the physics models in this review, this model has proven to predict mass flow, power and discharge temperature fairly accurately, only second to the model from Wang *et al.* (2008), which has a more complicated set of equations and accounts for refrigerant leakage. Direct comparison should be taken with the understanding that a different set of data is being used for these models, despite having the same refrigerant and compressor type.

Cambio (2016) proposed a fully empirical 23-coefficient model but found that only 5-11 factors were statistically significant, which is supported by the Marchante-Avellaneda *et al.* (2023) model in which less is more.

Tello-Oquendo *et al.* (2017) modified the AHRI model by adding an extra term to consider injection pressure and introduced a simple injected mass flow correlation to intermediate pressure which is inspired by Navarro *et al.* (2013). With this simple modification, they found maximum percent errors (MaxPE) of 4.4%, 1.8% and 2.9% for power, suction MFR and injection MFR, respectively. Then in 2019, Tello-Oquendo *et al.* (2019) developed a semi-empirical model for VI compressors, utilizing the same injected mass flow correlation to intermediate pressure and accounting for compressor speed. The model includes 6 fitted coefficients and physical properties such as heat coefficient from ambient temperature, leak area inside the compressor, volume ratio and electric efficiency which are design parameters determined by superheat, pressure, volumetric efficiencies etc. Results show improved or comparable prediction accuracies over physics-based models. However, compared to their 2017 empirical model, the 2019 semi-empirical model did not improve and performed relatively the same. A limited study was also performed on the effect of injection superheat on the model. The study showed the maximum deviations for the injection MFR, compressor power and discharge temperature were 3%, 3% and 2K respectively, which is promising, but more samples are desired to further prove and verify the model. Additionally, even though the model accounts for variable speed, it is not clear whether variable speed was tested.

The compressor model from Christ *et al.* (2022) takes inspiration from the models of Winandy and Lebrun (2002) and Tello-Oquendo *et al.* (2019) to combine the two-step adiabatic process and the pressure ratio relation to injection mass flow. This model provides an “optional” injector which suggests this model application for VI and non-VI compressors. Data from Christ *et al.* (2022) points out the injection mass flow relation to pressure ratio presented by Tello-Oquendo *et al.* (2019) only applies at constant compressor speeds. This is supported by Hjortland and Crawford (2023) but conflicts with Sjoholm *et al.* (2022). Christ *et al.* (2022) also show results as efficiencies or normalized values which are analogous to the MFR, power and discharge temperature. Maximum relative error is high for the power consumption, which may be problematic for confirming absolute values, but this model was able to demonstrate extrapolation of data with a relatively small increase in maximum error for the MFR and discharge temperature. Although the metrics are not identical and therefore, a direct comparison cannot be made, if the Christ model is compared to the Winandy and Lebrun model, the semi-empirical model may be better in terms of MFR but worse in terms of power. Results are not shown for the injection flow rate. A key concern with this model is the use of physical compressor specifications (e.g. efficiencies, losses) that would not commonly be shared by a compressor manufacturer; this contrasts the AHRI model whose coefficients reveal no physical information about the product.

Ziviani *et al.* (2017) proposed an ANN model which was compared to the Lumpkin *et al.* (2017) Buckingham PI semi-empirical model. Results for the ANN model shows suction mass flow, injected mass flow, power, and discharge temperature MAPEs (maximum absolute percent error) of 1.2%, 2.6%, 0.5% and 0.2%, respectively. For the semi-empirical model, the results are 1.8%, 13.8%, 0.5% and 0.3%, respectively. The proposed model essentially performs the same in power and discharge temperature, performs slightly better in terms of suction mass flow and performs significantly better in injection mass flow. The same comparison is done for two-phase injection, a configuration rarely explored in the research and shows that, for such a case, the ANN model cannot accurately predict injection mass flow or power. Zendehboudi *et al.* (2017) also incorporates ANN and Adaptive Neuro Fuzzy Inference System (ANFIS) to model a variable speed scroll compressor with VI. Comparing the two models, the ANFIS model performs the same or better than the ANN model, especially with the injection flow rate prediction. They also show the mean square error of the model with varying hidden layers, which shows that for six inputs and five outputs, nine hidden layers gives the lowest mean square error. Although the results are promising, one point of criticism that should be addressed is the fact that more than double the amount of the validation data was used to train the model.

Feng *et al.* (2009) explores a physics-based model of a scroll compressor using liquid injection and reports decent uncertainty in predicting power and discharge temperature. However, at evaporating temperatures below -30°C, the accuracy of the model “cannot be guaranteed.” The two-point prediction method from Lee *et al.* (2022) may help with this issue as it would divide the model into two operating regions to predict the parameters.

Table 2: Vapor Injection Literature

Author	Injection Type	Refrigerant / Compressor	Model Type	Details	% Error
Christ *et al.*, 2022	Vapor	R410A / Scroll	Semi-empirical	-Variable speed	3.3% Volumetric efficiency MaxPE 7.5% Compressor efficiency MaxPE 1.8% Discharge efficiency MaxPE
Dardenne *et al.*, 2015	Vapor	R410A / Scroll	Semi-empirical	-Variable speed	6.75% Suction MFR MaxPE 7.75% Inj MFR MaxPE 7.46% Power MaxPE 9.13K Discharge MaxAE
Dechesne *et al.*, 2015	Vapor	Scroll	Empirical	-Variable speed	99.9% Suction MFR R^2 94.3% Inj MFR R^2 98.4/95.6% Power R^2
Feng *et al.*, 2009	Liquid	R22 / Scroll	Physics		7% Power MaxPE 9K Discharge MaxAE
Hjortland *et al.*, 2023	Vapor	R410A, R407C / Scroll	Semi-empirical	-4 datasets*	1.9% Suction MFR MAPE 6.1% Inj MFR MAPE 1.9% Power MAPE 3.7K Discharge MaxAE
Kim *et al.*, 2017	Vapor	R410A / Scroll	Physics	-Variable speed	3% Suction MFR MaxPE 7% Inj MFR MaxPE 5% Power MaxPE 3K Discharge MaxAE
Lumpkin *et al.*, 2017	Vapor	R407C / Scroll	Semi-empirical	-Variable speed	1% Volumetric efficiency MaxPE 2% Isentropic efficiency MaxPE
Ning *et al.*, 2023	Vapor 2-phase	R410A / Rotary	Physics	-Variable speed	5% Power MaxPE 5K Discharge MaxAE
Park *et al.*, 2002	Vapor	R22 / Scroll	Physics	-Variable speed	7.5% Power MaxPE 10% Discharge MaxPE
Tello-Oquendo *et al.*,2019	Vapor	R407C / Scroll	Semi-empirical	-Variable speed term	1.95% Suction MFR MaxPE 3.97% Inj MFR MaxPE 4.47% Power MaxPE 3.24K Discharge MaxAE
Tello-Oquendo *et al.* 2017	Vapor	R407C / Scroll	Empirical		1.8% Suction MFR MaxPE 2.91% Inj MFR MaxPE 4.4% Power MaxPE 3.13% Inj Pressure MaxPE
Wang *et al.*, 2008	Vapor	R22 / Scroll	Physics		3% MFR MaxPE 4% Inj MFR MaxPE 4% Power MaxPE 2% Discharge MaxPE
Winandy and Lebrun, 2002	Vapor Liquid	R22 / Scroll	Physics		4.5% Suction MFR (13.5% w/ Liquid Inj) MaxPE 4.5% Power MaxPE 5K Discharge MaxAE
Zendehboudi *et al.*, 2017	Vapor	R410A / Scroll	Empirical	-ANN -AFNSI -Variable speed	ANN vs AFNSI 2.2% vs 2.3% MFR MaxPE 12.7% vs 4.1% Inj MFR MaxPE 2.4% vs 1.7% Power MaxPE 2.5% vs 2% Discharge MaxPE
Ziviani *et al.*, 2018	Vapor 2-phase	R407C / Scroll	Empirical	-ANN	1.2% Suction MFR MAPE 2.6% Inj MFR MAPE 0.5% Power MAPE 0.2% Discharge MAPE

*Absolute average taken for errors across datasets where multiple are available

The landscape of VI maps shows an even interest in the three types of models. There are gaps in the literature space where more liquid and two-phase injection testing is needed as well as modeling for those injection types. Tello-Oquendo *et al.* (2017, 2019) points out the relation between pressure ratio and injection MFR but two out of three identified sources state this is also dependent on frequency. Models are just starting to be applied to other types of injection such as liquid injection with the model from Winandy and Lebrun (2002) but this is physics-based. One of the best results that modeled injection flow rate well was the Ziviani *et al.* (2017) ANN model but took 80% of the available data to train the model. In this regard, the Tello-Oquendo *et al.* (2019) semi-empirical model may be the best model thus far in terms of accuracy to required training points. In any case, either injection flow rate or power has the highest uncertainty and it may be worth making direct comparisons with these models.

5. CONCLUSIONS

There is a growing need for improved VI compressor models for the design of heat pump systems. There are a number of documented compressor models in the research, both with and without VI. The quantity and sampling approach of measurements are important and testing burden can vary significantly depending on the model being fitted. While the AHRI 540 10-coefficient model has been very successful as a tool to communicate compressor performance information and make predictions in simulation/design tools, the current approach cannot reasonably be extended to include additional variables that are increasingly important: vapor injection pressure, frequency, superheat, and ambient temperature. Several publications have produced improved models that incorporate some of these independent variables, but insufficient data has been shown to demonstrate successful predictions across a wide range of *all* these varying parameters.

It is also important to consider that compressor models are most often used in the context of a system simulation software that iteratively solves the compressor along with an assortment of other components that comprise a vapor compression cycle. As such, a fast, smooth, continuous, predictable behavior is essential for integration into these tools. An area for concern with machine learning models is the potential for disjointed and nonlinear behaviors without physical basis that could prevent a system solver from achieving convergence. An increasing interest in transient modeling means that dynamic models of VI compressors must be developed alongside steady state ones. Furthermore, models that utilize physical parameters like displacement volume, volume ratio, efficiency, and loss terms will likely fail to gain traction due to manufacturer resistance to disclose proprietary details. Semi-empirical models like those of Tello-Oquendo, Cambio, and Hjortland and Crawford achieve high levels of predictive power while using coefficients that do not directly betray proprietary physical specifications. These approaches provide a solid foundation that can be expanded on to include dependence on all six relevant variables highlighted here.

A review of the literature also reveals gaps in testing and modeling of liquid and two-phase injection. It would be prudent to develop models that can be extended to any injection state. Planned future work includes fabrication of a test facility with a calorimeter and an in-depth test suite of a sampling of multiple VI compressors including changes in compressor frequency, injection pressure, superheat and ambient temperature. Comparisons will be made between various sampling methods, existing modeling methods and new approaches proposed by the authors.

NOMENCLATURE

HVAC	Heating, Ventilation, Air Conditioning	(-)
COP	Coefficient of Performance	(-)
VI	Vapor Injection	(-)
AHRI	Air-conditioning, Heating, and Refrigeration Institute	(-)
DOE	Design of Experiments	(-)
LHS	Latin Hypercube Spacing	(-)
PDOE	Polynomial Design of Experiments	(-)
SP-DOE	Scaling Polytope Design of Experiments	(-)
MaxPE	Maximum Percent Error	(-)
MaxAE	Maximum Absolute Error	(-)
MPE	Mean Percent Error	(-)
MAE	Mean Absolute Error	(-)
MAPE	Mean Absolute Percent Error	(-)

MAMWE	Maximum Average Mean Weighted Error	(-)
R^2	Coefficient of Determination	(-)
ANN	Artificial Neural Network	(-)
ANFIS	Adaptive Neuro Fuzzy Inference System	(-)
OEM	Original Equipment Manufacturer	(-)
TSNMA	Training Sample Normalized Model Accuracy	(-)
MFR	Mass Flow Rate	(-)

REFERENCES

Aute, V., Martin, C., & Radermacher, R. (2015). AHRI-8013 Final Report. *Air-Conditioning, Heating, and Refrigeration Institute (AHRI)*. http://www.ahrinet.org/App_Content/ahri/files/RESEARCH/Technical%20Results/AHRI-8013_Final_Report.pdf

Belman-Flores, J. M., Ledesma, S., Barroso-Maldonado, J. M., & Navarro-Esbrí, J. (2015). A comparison between the modeling of a reciprocating compressor using artificial neural network and physical model. *International Journal of Refrigeration*, *59*, 144–156. https://doi.org/10.1016/j.ijrefrig.2015.07.017

Byrne, P., Ghoubali, R., & Miriel, J. (2014). Scroll compressor modelling for heat pumps using hydrocarbons as refrigerants. *International Journal of Refrigeration*, *41*, 1–13. https://doi.org/10.1016/j.ijrefrig.2013.06.003

Cambio, M. (2016). Seminar 13—Advancements in Compressor Design, Testing and Performance Modeling for New Efficiency Standards and Alternative Refrigerants | *ANS: In Partnership with Techstreet*. https://www.techstreet.com/ans/standards/seminar-13-advancements-in-compressor-design-testing-and-performance-modeling-for-new-efficiency-standards-and-alternative-refrigerants?product_id=1921958

Christ, J., Schmid, F., Stergiaropoulos, K., & Bertsch, S. (2022). Semi-empirical Scroll Compressor Model with Optional Vapor-injection. *International Compressor Engineering Conference.*Cuevas, C., & Lebrun, J. (2009). Testing and modelling of a variable speed scroll compressor. *Applied Thermal Engineering*, *29*(2–3), 469–478. https://doi.org/10.1016/j.applthermaleng.2008.03.016

Dabiri, A. E., & Rice, C. K. (1981). Compressor-simulation model with corrections for the level of suction gas superheat (CONF-810657-2). Oak Ridge National Lab., TN (USA); Science Applications, Inc., La Jolla, CA (USA). https://www.osti.gov/biblio/6345140

Dardenne, L., Fraccari, E., Maggioni, A., Molinaroli, L., Proserpio, L., & Winandy, E. (2015). Semi-empirical modelling of a variable speed scroll compressor with vapour injection. *International Journal of Refrigeration*, *54*, 76–87. https://doi.org/10.1016/j.ijrefrig.2015.03.004

Dechesne, B., Bertagnolio, S., & Lemort, V. (2015). Development of an empirical model of a variable speed vapor injection compressor used in a Modelica-based dynamic model of a residential air source heat pump. *IOP Conference Series: Materials Science and Engineering*, *90*, 012031. https://doi.org/10.1088/1757-899X/90/1/012031

Feng, C., Jiyou, F., Ziwen, X., & Liansheng, L. (2009). Study on performance of a heat pump water heater using suction stream liquid injection. *Applied Thermal Engineering*, *29*(14–15), 2942–2948. https://doi.org/10.1016/j.applthermaleng.2009.03.001

Guo, Y., Li, G., Chen, H., Hu, Y., Shen, L., Li, H., Hu, M., & Li, J. (2017). Development of a virtual variable-speed compressor power sensor for variable refrigerant flow air conditioning system. *International Journal of Refrigeration*, *74*, 73–85. https://doi.org/10.1016/j.ijrefrig.2016.09.025

Hjortland, A. L., & Crawford, R. R. (2023). Simplified steady-state modeling of positive displacement compressors. *International Journal of Refrigeration*, *159*, 333–343. https://doi.org/10.1016/j.ijrefrig.2023.12.038

Hjortland, A. L., & Crawford, R. R. (2024). A comparative analysis of a new semi-empirical model and the AHRI polynomial model for positive displacement compressors. *International Journal of Refrigeration*, *159*, 254–263. https://doi.org/10.1016/j.ijrefrig.2023.12.009

Jähnig, D. I., Reindl, D. T., & Klein, S. A. (2000). A Semi-Empirical Method for Representing Domestic Refrigerator/Freezer Compressor Calorimeter Test Data.

Kim, D. (2017). Optimization of the injection-port geometries of a vapor injection scroll compressor based on SCOP under various climatic conditions. *Energy*, *135*, 442–454. http://dx.doi.org/10.1016/j.energy.2017.06.153Lee, C.-Y., Cao, T., Hwang, Y., Radermacher, R., & Shaffer, S. (2021). Development of accurate and widely applicable compressor performance maps. *IOP Conference Series: Materials Science and Engineering*, *1180*(1), 012041. https://doi.org/10.1088/1757-899X/1180/1/012041

Lee, C., Hwang, Y., & Shaffer, S. (2022). An Improved Mass Flow Rate Prediction Method for Rolling Piston Compressors. *International Compressor Engineering Conference*. https://docs.lib.purdue.edu/icec/2779Lee, C. K., & Lam, H. N. (2013). A comparison of different generalised modelling approaches for a scroll refrigerant compressor. *International Journal of Refrigeration, 36*(4), 1369–1375. https://doi.org/10.1016/j.ijrefrig.2013.01.002

Li, W. (2012). Simplified steady-state modeling for hermetic compressors with focus on extrapolation. *International Journal of Refrigeration, 35*(6), 1722–1733. https://doi.org/10.1016/j.ijrefrig.2012.03.008

Lumpkin, D., Spielbauer, N., & Groll, E. (2017). Performance Measurements and Mapping of a R-407C Vapor Injection Scroll Compressor. *IOP Conf. Series: Materials Science and Engineering, 232*. https://doi.org/doi:10.1088/1757-899X/232/1/012049Ma, J., Ding, X., Horton, W. T., & Ziviani, D. (2020). Development of an automated compressor performance mapping using artificial neural network and multiple compressor technologies. *International Journal of Refrigeration, 120*, 66–80. https://doi.org/10.1016/j.ijrefrig.2020.08.001

Mackensen, A., Klein, S. A., & Reindl, D. T. (2002). Characterization of Refrigeration System Compressor Performance. International Refrigeration and Air Conditioning Conference. http://docs.lib.purdue.edu/iracc/567Marchante-Avellaneda, J., Corberan, J. M., Navarro-Peris, E., & Shrestha, S. S. (2023). A critical analysis of the AHRI polynomials for scroll compressor characterization. *Applied Thermal Engineering, 219,* 119432. https://doi.org/10.1016/j.applthermaleng.2022.119432

Navarro-Peris, E., Corberán, J. M., Falco, L., & Martínez-Galván, I. O. (2013). New non-dimensional performance parameters for the characterization of refrigeration compressors. *International Journal of Refrigeration, 36*(7), 1951–1964. https://doi.org/10.1016/j.ijrefrig.2013.07.007

Ning, Q., Sun, W., He, G., Cai, D., Li, X., & Zhang, Z. (2023). Investigation on improving the heating performance of a heat pump using a rotary compressor with vapor and two-phase injection. *Energy Conversion and Management, 278,* 116703. https://doi.org/10.1016/j.enconman.2023.116703

Ossorio, R., & Navarro-Peris, E. (2023). Testing of Variable-Speed Scroll Compressors and their inverters for the evaluation of compact energy consumption models. *Applied Thermal Engineering, 230,* 120725. https://doi.org/10.1016/j.applthermaleng.2023.120725

Park, Y. C., Kim, Y., & Cho, H. (2002). Thermodynamic analysis on the performance of a variable speed scroll compressor with refrigerant injection. *International Journal of Refrigeration, 25*(8), 1072–1082. https://doi.org/10.1016/S0140-7007(02)00007-5

Sjoholm, L., & Ma, Y. C. (2018). A Study of Low GWP Refrigerants for Transport Refrigeration based on Hermetic Scroll Compressors with an Economizer. *International Compressor Engineering Conference.*Tello-Oquendo, F. M., Navarro-Peris, E., & Gonzálvez-Maciá, J. (2017). New characterization methodology for vapor-injection scroll compressors. *International Journal of Refrigeration, 74,* 528–539. https://doi.org/10.1016/j.ijrefrig.2016.11.019

Tello-Oquendo, F. M., Navarro-Peris, E., Barceló-Ruescas, F., & Gonzálvez-Maciá, J. (2019). Semi-empirical model of scroll compressors and its extension to describe vapor-injection compressors. Model description and experimental validation. *International Journal of Refrigeration, 106,* 308–326. https://doi.org/10.1016/j.ijrefrig.2019.06.031

Wang, B., Shi, W., Li, X., & Yan, Q. (2008). Numerical research on the scroll compressor with refrigeration injection. *Applied Thermal Engineering, 28*(5–6), 440–449. https://doi.org/10.1016/j.applthermaleng.2007.05.012

Winandy, E. (2002). Experimental analysis and simpli®ed modelling of a hermetic scroll refrigeration compressor. *Applied Thermal Engineering, 22,* 107–120.Winandy, E. L., & Lebrun, J. (2002). Scroll compressors using gas and liquid injection: Experimental analysis and modelling. *International Journal of Refrigeration, 25*(8), 1143–1156. https://doi.org/10.1016/S0140-7007(02)00003-8

Zendehboudi, A., Li, X., & Wang, B. (2017). Utilization of ANN and ANFIS models to predict variable speed scroll compressor with vapor injection. *International Journal of Refrigeration, 74,* 475–487. https://doi.org/10.1016/j.ijrefrig.2016.11.011

Ziviani, D., Bahman, A. M., James, N. A., Lumpkin, D., & Braun, J. E. (2018). Machine Learning Applied to Positive Displacement Compressors and Expanders Performance Mapping. *International Compressor Engineering Conference.*

ACKNOWLEDGEMENT

This material is based upon work supported by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under the Building Technologies Office Award Number DE-EE0010906.