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Limits of modeling approach for refrigerant charge assessment

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Abstract

Given their performance, heat pumps are a key technology to decarbonize the heating production in buildings. Their share in the residential heating market is increasing at a very fast pace, making preventive maintenance and, thus, automatic fault detection and diagnosis always more necessary, especially to maintain an optimum efficiency and lighten the load for installers-maintainers. Soft and progressive faults such as refrigerant leakages must therefore be detected before they deteriorate the performance of the system or even damage the components. Early detection of leakages and real-time quantification of the refrigerant charge is thus a major challenge.
Several methods for assessing refrigerant leaks have been developed. Most rely on a statistical approach, where an empirical relationship is established between the refrigerant amount in the system and other features. Such methods can be rather accurate, but rely on a significant amount of experimental data for their calibration. Thus, developing a physical model of the system to generate the training data numerically seems to be a very promising lead. It also allows to represent the distribution of the refrigerant charge in the various heat pump components and thus better understand the system's behaviour.
Developing such a model is however not an easy task, as several components containing a significant amount of refrigerant are very difficult to model accurately due to the often unknown internal geometry. Many models neglect these components or make highly simplifying assumptions. Therefore, in a first part, this study aims to describe the problematic components, in particular the suction accumulator and the filter, to study their modeling and the associated uncertainty. In a second part, the objective is to assess the consequences of incorrectly taking the characteristics of these components into account on the quantification of the total charge in the heat pump.

Keywords: smart heat pump ; predictive maintenance ; refrigerant charge assessment ; modeling

1. Introduction

The growing share of heat pump (HP) sales in the heating sector makes it important to lighten the workload for installers and maintainers. One promising approach is the development of smart HPs, which are able to both determine their performance in real time and implement predictive maintenance. The latter aims at automatically detecting and diagnosing soft faults (which do not immediately lead to the system shutdown unlike hard faults) before they become too critical, in order to prepare and prioritize maintenance interventions. Among soft faults, refrigerant leaks are particularly impactful, as they significantly degrade system performance. However, this impact on performance typically becomes noticeable only after a substantial loss of refrigerant – ranging from 30% to 50% of the nominal charge – depending on the quality of the HP's control systems [1], [2].

Detecting and quantifying a refrigerant leakage is thus a complex task, typically carried out by monitoring the internal operating parameters of the HP, such as refrigerant pressures and temperatures. A key indicator – often subcooling [3] – is used as a charge-sensitive feature to estimate the refrigerant level under specific operating conditions. The evaporator inlet vapor quality can also be a very interesting alternative when subcooling is minimal or zero [4]. Other features representative of the operating condition must be considered to distinguish whether variations in this charge-sensitive feature are due to an actual leakage or simply changes in external factors, such as weather conditions or comfort temperature setpoints.

Previous studies have proposed empirical approaches establishing relationships between the refrigerant amount in the system and the selected features [5], [6]. However, these methods require extensive experimental data covering multiple charge levels and a wide range of operating conditions. Besides, this experimentation is very system-specific and must be conducted for each HP type, which makes these approaches costly and time-consuming.

To overcome this limitation, some authors such as Haddad [7] have proposed using a physical model of a HP to generate synthetic data to calibrate a charge prediction model. Such a model is based on detailed description of the HP components, including their dimensions, geometries and thermophysical characteristics, as well as physical phenomena occurring in each part of the system. Although complex to develop, physical models offer several advantages compared to purely empirical or black box approches:

- They provide deeper understanding of HP behavior and the underlying phenomena – particularly those related to refrigerant flow within the system and potential accumulation in certain components. This is especially true if the model supports a dynamic approach, which allows the observation of transient behaviors and refrigerant migration over time.
- They require limited experimental data for calibration and validation.

However, the necessity to accurately account for all refrigerant storage volumes and associated physical phenomena may limit the applicability and generality of this approach, as such detailed information is not always available.

This study therefore aims to assess the influence of the physical model accuracy on the overall performance of refrigerant charge prediction methods based on model-generated data. In other words, it focuses on quantifying how uncertainties or simplifications in the HP physical model affect the reliability of the resulting charge estimation. The first part of this work outlines the methodology applied for this numeric study: a reference model of the HP was developed and experimentally validated, with particular attention given to the main storage components and the uncertainties associated with their representation. This reference model was then intentionally degraded to generate data that reflects these uncertainties. In the second part, a charge-prediction model – trained on data from both the reference and the degraded models – is applied to reference test data to evaluate its performance under various conditions.

2. Methods

2.1. System studied and physical HP model

The system under study is a commercially available air-to-water heat pump with a heating capacity of 6 kW. The nominal refrigerant charge (R32), as specified by the manufacturer, is 1.3 kg for refrigerant line lengths below 15 meters. This heat pump is a split system, consisting of an outdoor unit and an indoor unit.

The outdoor unit of the HP includes:

- a fin-and-tube evaporator,
- a variable-speed twin rotary compressor with its suction accumulator,
- and an electronic expansion valve (EEV) regulating discharge superheat around 35 K. This control strategy is particularly relevant for R32 refrigerant, which tends to reach high discharge temperatures. As a result, it often leads to zero superheat at the compressor inlet.

The indoor unit consists of a plate condenser equipped with an outlet filter, and an indoor module, which includes the water circulation pump, an expansion tank, a domestic hot water tank, and backup heaters.
A physical model of this HP was developed using the software Dymola (based on the object-oriented Modelica language), and the library TIL (developed by TLK-Thermo GmbH) providing components for thermodynamic systems. The thermophysical properties of the working fluids – refrigerant, air, and water – are computed using the TILMedia tool, which is integrated into the TIL environment. TIL facilitates the assembly of components,

allowing users to define their geometry and select from a range of correlations for heat transfer and pressure drop calculations.

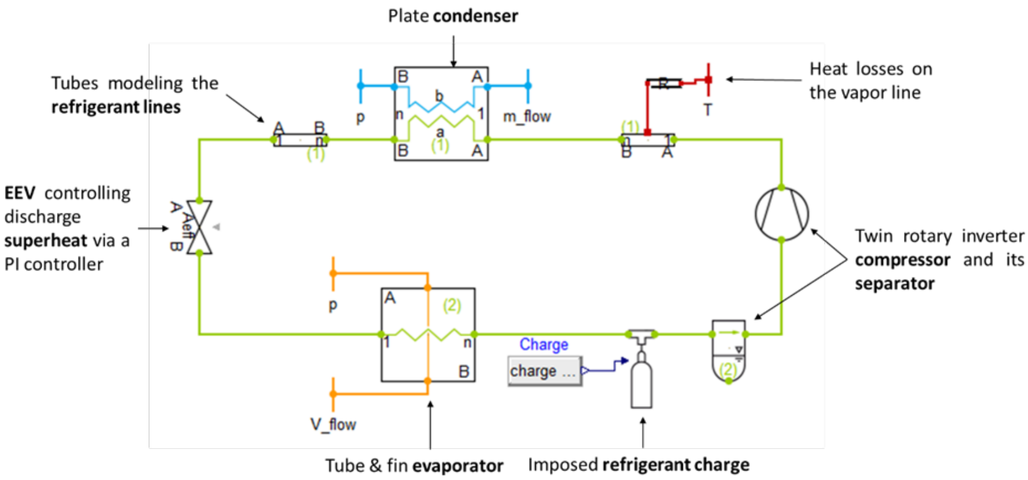

Figure 1. HP model.
Green lines represent refrigerant lines; the water loop is represented by the blue lines, and the air flow by the orange ones.

All components are modeled using a physical approach based on energy, mass, and momentum balance equations, allowing dynamic simulations. The only exception is the compressor, whose modeling instead relies on a mapping of its efficiencies based on data provided by the manufacturer.

The main components (compressor and heat exchangers) were first individually validated against experimental data, at a nominal charge and for a wide range of operating conditions. The inlet conditions of the refrigerant were imposed and the outlet conditions and main outcomes (condenser and evaporator capacities, compressor electric power, mass flow rate) were compared to their experimental counterparts. The whole model was then validated using both steady-state and dynamic experimental data, the latter obtained through a Hardware-in-the-Loop (HiL) test bench, across various refrigerant charge levels (from 80 to 110 % of the nominal charge). The relative errors were below 5 % for the main features of interest (mass flow rate, condenser capacity, compressor power, low and high pressures) ; they were slightly higher (7 %) for the evaporator capacity and the Coefficient of Performance (COP). The experimental observations confirmed the absence of superheat at the compressor inlet due to the use of R32. Besides, the HP appeared to be very well optimized, as subcooling was rather low at nominal charge (3-5 K) and quickly dropped to zero after a small loss of refrigerant.

However, the model could not be validated for charge levels below 80 % of the nominal charge. This is because, in a closed-loop system, both the total refrigerant charge and its distribution among components are critical to determining the overall system performance. It can therefore be inferred that discrepancies at lower charge levels likely stem from inadequate modeling of refrigerant storage phenomena. Several components may have contributed to this issue. Heat exchangers typically store a significant amount of refrigerant, but they have been extensively studied in the literature, particularly in relation to void fraction correlations [8]. This study therefore shifts focus to ancillary components, which are less commonly addressed but can also contribute substantially to refrigerant storage. Their modeling approaches and associated limitations are discussed below.

2.1.1. Suction accumulator

The suction accumulator is typically not considered a critical component in HP modeling, as it usually contains little refrigerant due to the superheated vapor state at the compressor inlet. However, with R32 refrigerant, the absence of superheat at the evaporator outlet results in a two-phase flow entering the suction accumulator, which then becomes filled with liquid refrigerant. This makes accurate knowledge of its internal volume and vapor-liquid equilibrium particularly important.

In standard configurations, a suction accumulator model has one inlet and two outlets (liquid and vapor), though in this study, only the vapor outlet was used. The model estimates the state of the refrigerant at the component outlet based on its geometry and inlet flow characteristics (pressure, velocity, vapor quality, etc.). While this problem usually requires Computational Fluid Dynamics (CFD) for precise resolution, a simplified ideal separation approach was adopted: below a given liquid filling level, pure vapor is assumed at the outlet; above this threshold, a two-phase flow is modeled with interpolated vapor quality between 1 and 0, as illustrated in Figure 2 (illustrating an upper threshold of 90%).

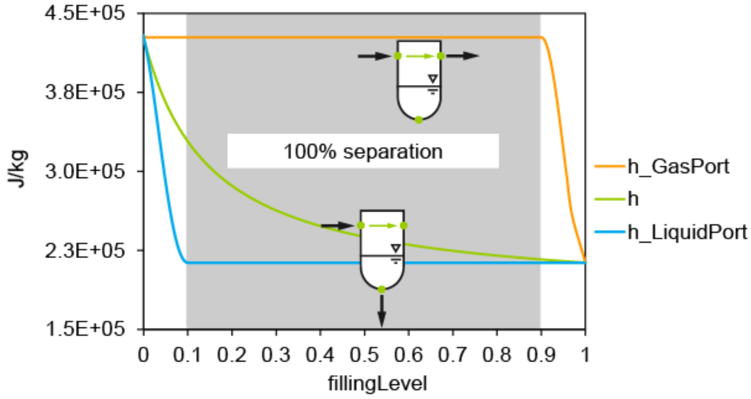

Figure 2. Ideal separation characteristic for the suction accumulator.
Source: TIL documentation.

The effective internal volume of the suction accumulator can usually be provided by the manufacturer. But even with an accurate estimation of this volume, which was the case for this study, the separation characteristic between vapor and liquid phases could not be accurately depicted. The ideal separation assumption may lead to the overestimation of the liquid retention, especially under low charge conditions. However, developing a more realistic correlation would require extensive, refrigerant- and component-specific experimentation.

In this study, the suction accumulator stored approximately 40 % of the total refrigerant charge in the cycle, making it the system's primary storage component. Its modeling accuracy therefore has a significant impact on the overall performance of the HP model.

2.1.2. Compressor crankcase and oil

The refrigerant can be stored in the compressor crankcase, in the form of vapor within the compressor shell, as well as refrigerant dissolved in the lubricating oil in the oil sump, owing to refrigerant-oil solubility. Thus, these two elements were considered :

- The volume of the crankcase was estimated based on an internal study at EDF R&D, assuming that it represents approximately 40 % of the compressor's internal volume. The charge located in the crankcase (apart from that trapped in the lubricating oil) is therefore calculated by multiplying this volume (minus the volume occupied by the oil) by the density of the refrigerant at the compressor outlet. Numerically, about 4 % of the total refrigerant charge was located in the crankcase, depending on the operating conditions.
- The amount of refrigerant dissolved in the oil inside the crankcase can also be significant. Modeling this phenomenon requires to estimate the solubility of the refrigerant in the lubricating oil, which depends on the discharge pressure and temperature. Researchers have established tables for the solubility of R32 with different oils [9], [10], [11] for different pressures and temperatures. A compromise between these tables was first implemented in the model in the form of a table of values, interpolating the oil retention rate (defined by the mass of refrigerant trapped in oil divided by the total mass of oil plus refrigerant trapped) as a function of pressure and temperature, and tested. To enhance the robustness of the model, a compromise relying on a fixed oil retention rate of 15 % was selected, as variations around this value had minimal impact on the amount of refrigerant dissolved and on the behavior of the model. Using this value, about 6 % of the total charge was trapped in the lubricating oil, on average over the different operating conditions.

Even with detailed diagrams, the crankcase internal volume is difficult to determine accurately. In addition, modeling the solubility of the refrigerant in the lubricating oil is uncertain as well. Numerically, when considering both the refrigerant in the crankcase and that trapped in the lubricating oil, about 10 % of the total charge was located in the compressor crankcase.

2.1.3. Condenser filter

The liquid line typically contains a significant amount of refrigerant due to the latter typically being in liquid state. But one component may be particularly critical: the filter located at the condenser outlet. While its external dimensions are relatively easy to obtain, estimating its internal volume is more challenging due to the uncertain filling ratio of the filtering particles (see Figure 3).

Figure 3. A dissected liquid line filter (length: approx. 10 cm).

This makes it difficult to accurately assess the amount of refrigerant stored within the filter. Numerically, about 10 to 20 % of the total charge was located in this filter, depending on whether there was subcooling or not at the condenser outlet.

2.2. Refrigerant charge prediction model

Based on the previous observations, it is essential to evaluate the impact of inaccurately characterizing these components on the quantification of the total charge in the HP when applying a charge prediction model. To do so, a charge prediction model was developed:

- Regression method: Histogram Gradient Boosting (HGB) regressor. In this study, other methods such as polynomial regression and support vector regression (SVR) were also tested, but HGB was chosen because it offers an excellent compromise between accuracy and computational efficiency. Its histogram-based binning enables fast training, making it particularly well-suited when large training datasets are available.
- Charge-sensitive features: subcooling and evaporator inlet vapor quality. Indeed, most charge prediction models use subcooling, but the latter is minimal for this well-optimized HP, and quickly drops to zero for a slightly undercharged system, making it insuficient. Evaporator inlet vapor quality already proved to be a very interesting charge-sensitive feature for refrigerant charge prediction when subcooling is minimal [4]. Although it cannot be directly measured in experimentation, it can be estimated from the calculated mass flow rate – derived using the compressor energy balance and compressor mapping – combined with water-side measurements at the condenser and the low-pressure value.
- Other input features, representative of the operating condition of the HP: low and high pressures and compressor frequency. These were selected based on a study on the relative importance of different combinations of features to improve the performance of the charge prediction model.

2.3. Training and testing data

The experimentally validated HP model was used as a reference model, deemed as a perfect representation of the real system, while degraded models derived from this reference model were generated to account for the uncertainties on the modeling of the filter, cranckase and suction accumulator. To do so, the internal volumes of these components were either underestimated or overestimated.

Several sets of training data were thus generated from the reference model and its degraded versions:

- Dataset 0: A reference training dataset, generated by the reference model. The crankcase volume was considered to represent 40 % of the total internal volume of the compressor, and the suction accumulator's thresholds for ideal separation were set to 20 and 80 %.
- Degraded datasets, obtained with degraded models presenting the following features:
  - Dataset 1: Overestimation of the filter's internal volume of 10 %
  - Dataset 2: Underestimation of the filter's internal volume of 10 %
  - Dataset 3: Overestimation of the crankcase's internal volume of 25 %
  - Dataset 4: Underestimation of the crankcase's internal volume of 25 %
  - Dataset 5: Thresholds in the suction accumulator of 10 and 90 %
  - Dataset 6: Thresholds in the suction accumulator of 30 and 70 %
  - Dataset 7: Underestimation of the filter's internal volume of 10 % + thresholds in the suction accumulator of 10 and 90 %
  - Dataset 8: Overestimation of the filter's internal volume of 10 % + thresholds in the suction accumulator of 10 and 90 %

The variations in the filter's internal volume actually essentially account for the uncertainty in its filling ratio. The ±25 % variation of the internal volume of the crankcase is intended to also capture the uncertainty related to oil retention, and was actually calculated by considering that the crankcase volume could represent from 30 to 50 % of the total internal volume of the compressor. Finally, the suction accumulator's minimal and maximal thresholds were adjusted to account for uncertainties in vapor-liquid separation behavior.

The range of conditions covered by these training datasets are presented in Table 1, making a total of 960 different points:

Table 1. operating conditions for the training datasets

	Min	Max	Step
Refrigerant charge level (% of nominal charge)	80	110	2
Outdoor temperature (°C)	-10	10	5
Return water temperature (°C)	30	50	10
Compressor Frequency (Hz)	40	100	20

The testing dataset was generated using the reference HP model, with operating conditions randomly sampled – following a uniform distribution – within the same ranges defined for each feature in Table 1. This dataset is supposed to represent the on-field operation of the real HP.

The charge prediction model was then calibrated using the reference dataset and the degradated datasets, and applied on the same testing dataset.

3. Results and discussion

The indicators chosen to assess the performance of the charge prediction are the Mean Relative Error (MRE, %), the Mean Absolute Error (MAE, in gram), the R^2 coefficient, the relative Mean Bias Error (MBE (rel), %), and the percentage of predictions within an error range of ±5 %.

3.1. Reference scenario: training conducted on a perfect HP model (dataset 0)

Table 2. Performance of the charge prediction model trained on data from the reference HP model

	Training performance	Testing performance
Training: dataset 0	MRE = 0.72 % MAE = 9 g R^2 = 0.99 MBE (rel) = 0.02 % ±5% = 99.6 %	MRE = 1.50 % MAE = 19 g R^2 = 0.92 MBE (rel) = 0.26 % ±5% = 97.4 %

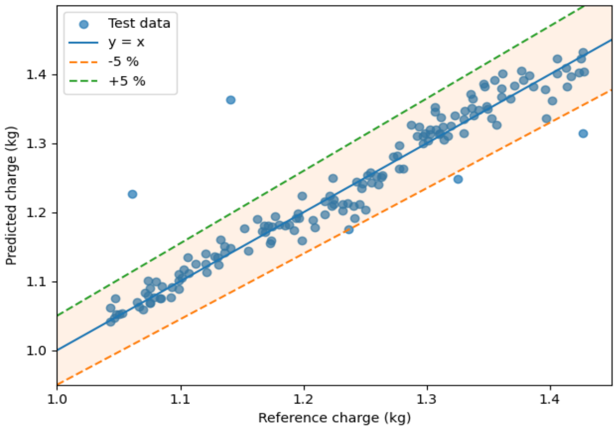

Figure 4. Charge prediction for the reference scenario (perfect HP model) applied on testing dataset

In the reference scenario, the charge prediction model is trained using data generated by the reference model and tested on the dataset generated by the same model. The performance is thus very high, with an error of 19 g (1.50 %), a very low bias (0.26 %) and almost all data (97.4 %) within an error range of ± 5 %.

3.2. Training conducted on degraded models – one component mischaracterized (datasets 1 to 6)

In all the scenarios considered, the training performance of the charge prediction model is very high, with average relative errors below 1 % and a R^2 coefficient superior to 0.99 (Table 3, Table 4, Table 5). It is thus clear that the differences observed in the testing performance results, compared to the reference scenario, can be solely attributed to the degraded HP models.

3.2.1. Modification of the filter

Table 3. Performance of the charge prediction model trained on data derived from a HP model affected by incorrect filter characterization.

	Training performance	Testing performance
Training: dataset 1, overestimated filter volume	MRE = 0.64 % MAE = 8 g R^2 = 0.99 MBE (rel) = 0.01 % ±5% = 99.6 %	MRE = 2.32 % MAE = 28 g R^2 = 0.87 MBE (rel) = 1.92 % ±5% = 96.1 %
Training: dataset 2, underestimated filter volume	MRE = 0.71 % MAE = 9 g R^2 = 0.99 MBE (rel) = 0.02 % ±5% = 99.5 %	MRE = 2.08 % MAE = 26 g R^2 = 0.89 MBE (rel) = -1.33 % ±5% = 95.4 %

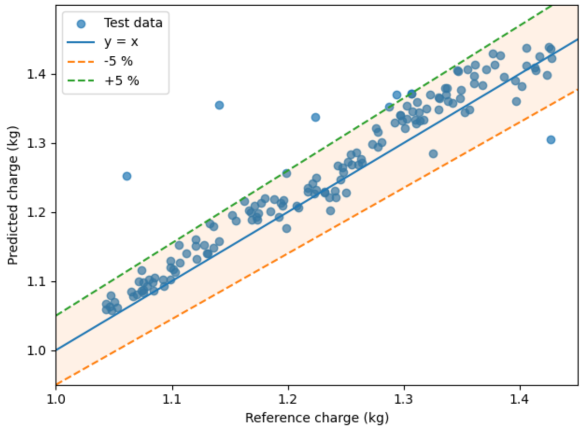

Figure 5. Charge prediction with a training conducted on a degraded HP model – overestimation of the filter volume

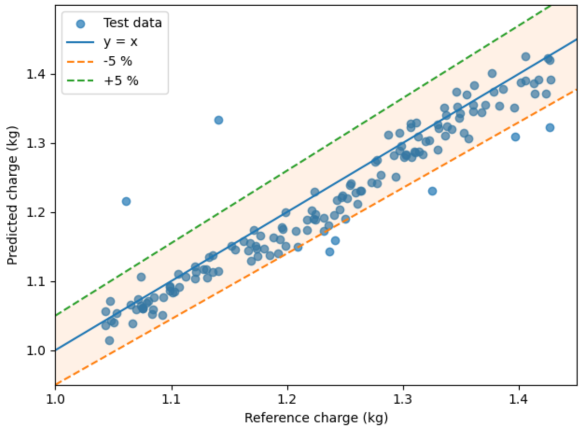

Figure 6. Charge prediction with a training conducted on a degraded HP model – underestimation of the filter volume

When the charge prediction model in trained on data generated with a HP model that incorrectly characterizes the internal volume of the filter (or, more precisely, its filling), the performance of the prediction is slightly deteriorated, with average relative errors of 2.32 % and 2.08 % (compared to 1.50 % in the reference case).

If the volume is overestimated, the model will tend to overpredict the refrigerant charge when applied to the test data (MBE slightly positive). Conversely, if the volume is underestimated, the model will underpredict the refrigerant charge in the test data (MBE slightly negative). This is logical: if the model is trained using a HP model that overestimates the total storage volume compared to the test model, it will overestimate the refrigerant amount in the test data.

As the refrigerant stored in the filter in the reference model accounted for 10-20 % of the total refrigerant charge, a variation of 10 % of the filter volume represents approximately 1-2 % of the total charge, which is consistent with the small additional error observed on the test data compared to the reference scenario.

3.2.2. Modification of the crankcase

Table 4. Performance of the charge prediction model trained on data derived from a HP model affected by incorrect crankcase characterization.

	Training performance	Testing performance
Training: dataset 3, overestimated crankcase volume	MRE = 0.65 % MAE = 8 g R^2 = 0.99 MBE (rel) = 0.02 % ±5% = 99.3 %	MRE = 1.78 % MAE = 22 g R^2 = 0.90 MBE (rel) = 0.95 % ±5% = 97.4 %
Training: dataset 4, underestimated crankcase volume	MRE = 0.70 % MAE = 9 g R^2 = 0.99 MBE (rel) = 0.02 % ±5% = 99.4 %	MRE = 1.73 % MAE = 22 g R^2 = 0.91 MBE (rel) = -0.61 % ±5% = 96.1 %

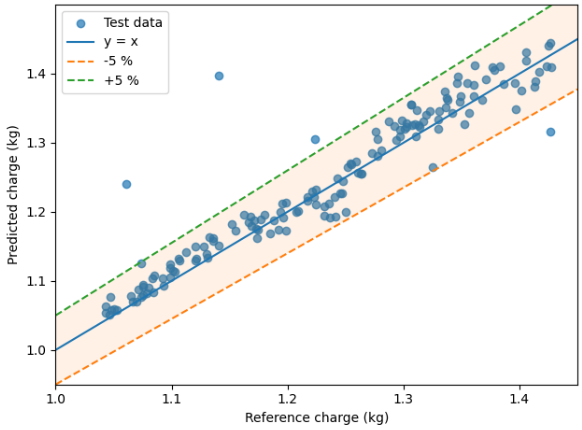

Figure 7. Charge prediction with a training conducted on a degraded HP model – overestimation of the crankcase volume

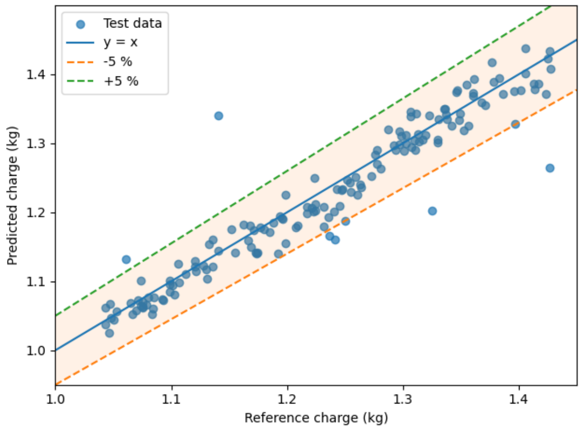

Figure 8. Charge prediction with a training conducted on a degraded HP model – underestimation of the crankcase volume

When the charge prediction model in trained on data generated with a HP model that incorrectly characterizes the internal volume of the crankcase, the performance of the prediction is almost unchanged (average relative errors of 1.78 % and 1.73 %, compared to 1.50 % in the reference scenario).

As the refrigerant stored in the crankcase and the oil in the reference model accounted for 10 % of the total refrigerant charge, a variation of 25 % of the crankcase volume represents approximately 2.5 % of the total charge. This is consistent with the small additional error observed on the test data compared to the reference scenario.

3.2.3. Modification of the suction accumulator

Table 5. Performance of the charge prediction model trained on data derived from a HP model affected by incorrect suction accumulator characterization.

	Training performance	Testing performance
Training: dataset 5, overestimated suction accumulator volume	MRE = 0.64 % MAE = 8 g R^2 = 0.99 MBE (rel) = 0.01 % ±5% = 99.5 %	MRE = 4.21 % MAE = 51 g R^2 = 0.73 MBE (rel) = 4.03 % ±5% = 69.3 %
Training: dataset 6, underestimated suction accumulator volume	MRE = 0.69 % MAE = 9 g R^2 = 0.99 MBE (rel) = 0.02 % ±5% = 99.4 %	MRE = 4.09 % MAE = 50 g R^2 = 0.72 MBE (rel) = -3.63 % ±5% = 71.9 %

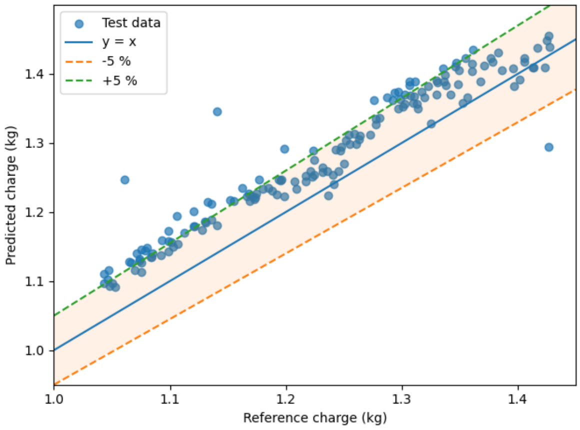

Figure 9. Charge prediction with a training conducted on a degraded HP model – overestimation of the suction accumulator volume

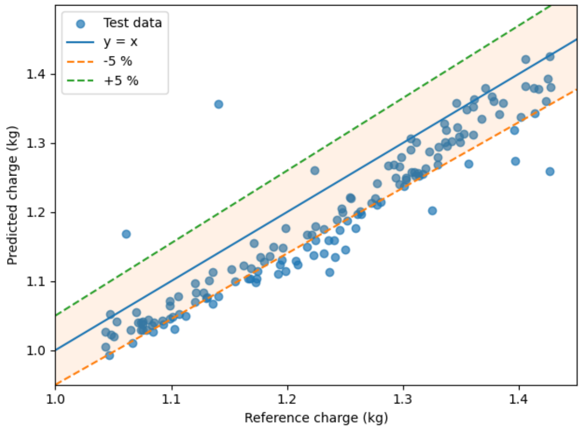

Figure 10. Charge prediction with a training conducted on a degraded HP model – underestimation of the suction accumulator volume

Finally, when the charge prediction model in trained on data generated with a HP model that incorrectly characterizes the suction accumulator, the performance of the prediction is quite deteriorated, with an effect much superior to that of an incorrect filter or crankcase characterization.

The same observations as with the filter can be made: if the internal volume of the suction accumulator is overestimated, the model will tend to overpredict the refrigerant charge when applied to the test data. Conversely, if the internal volume is underestimated, the model will underpredict the refrigerant charge in the test data. This is consistent with the values of the MBE indicator, which is positive (approx. 4 %) in the first case, negative in the second one (approx. -4 %).

As the refrigerant stored in the suction accumulator in the reference model accounted for 40 % of the total refrigerant charge, a variation of 10 % of the suction accumulator volume represents approximately 4 % of the total charge, which is consistent with the significant additional error observed on the test data compared to the reference scenario.

3.3. Training conducted on degraded models – two components mischaracterized (datasets 7 and 8)

Here again, where two components are mischaracterized, the charge prediction model demonstrates excellent training performance, with average relative errors below 1% and an R^2 coefficient exceeding 0.99 (Table 6). This confirms that any discrepancies observed in testing performance, when compared to the reference scenario, can be attributed solely to the degraded HP models.

Table 6. Performance of the charge prediction model trained on data derived from a HP model affected by incorrect filter and suction accumulator characterization.

	Training performance	Testing performance
Training: dataset 7, underestimated filter volume and overestimated suction accumulator volume	MRE = 0.68 % MAE = 8 g R^2 = 0.99 MBE (rel) = 0.02 % ±5% = 99.3 %	MRE = 2.92 % MAE = 35 g R^2 = 0.85 MBE (rel) = 2.56 % ±5% = 95.4 %
Training: dataset 8, overestimated filter and suction accumulator volumes	MRE = 0.63 % MAE = 8 g R^2 = 0.99 MBE (rel) = 0.02 % ±5% = 99.5 %	MRE = 5.53 % MAE = 67 g R^2 = 0.55 MBE (rel) = 5.42 % ±5% = 32.7 %

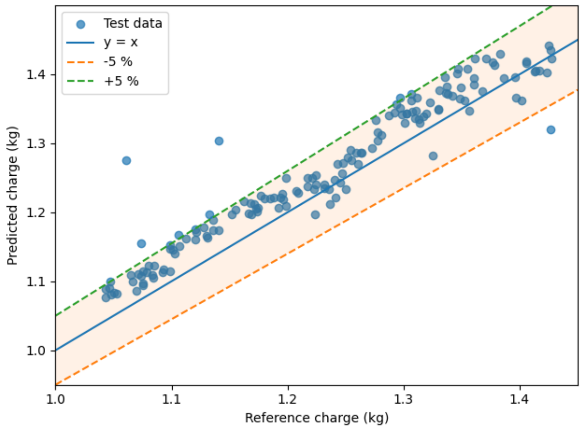

Figure 11. Charge prediction with a training conducted on a degraded HP model – underestimation of the filter volume and overestimation of the suction accumulator volume

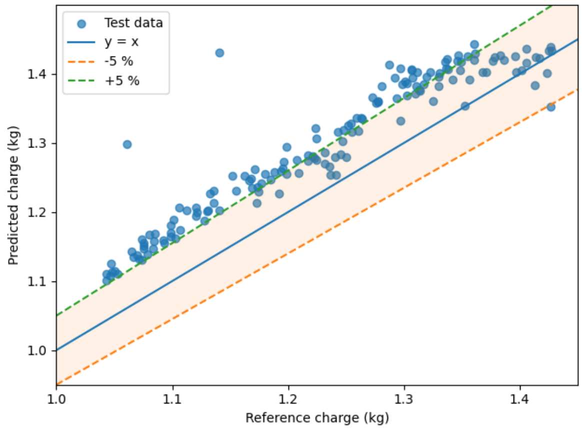

Figure 12. Charge prediction with a training conducted on a degraded HP model – overestimation of both the filter and the suction accumulator volumes

The errors can somehow compensate each other, as shown with dataset 7 where the filter volume is underestimated whereas the upper separation threshold in the suction accumulator in overestimated. In that case, the charge prediction error is still increased compared to that of the reference scenario, but remains acceptable (approx. 3 %).

Conversely, when the errors in the model add up as with dataset 8 where both the filter and the suction accumulator volumes are overestimated, the charge prediction model does not perform well, reaching an average error of about 5.5 % in this case. This combination of errors also strengthens the positive biases (MBE of 2.56 and 5.42 %).

3.4. Summary of the results and discussions

Based on these observations, the results can be summarized as follows:

- The compressor crankcase appears to have a negligible impact on the performance of the refrigerant charge prediction, whereas the suction accumulator shows the most significant influence.
- Prediction performance is affected by approximately up to 4% in cases of individual component error, and up to 5.5 % when multiple errors occur simultaneously.
- However, even if in some cases the average error on charge prediction can remain acceptable, the issue is that the model will systematically under- or overpredict the refrigerant charge.

Regarding the accumulator, the threshold used in the vapor-liquid separation law is not precisely known. In this study, this threshold was fixed arbitrarily in order to analyze its sensitivity with respect to the refrigerant charge prediction. In reality, the separation behavior is likely more complex, as the effective threshold is not only uncertain but may also vary with the operating conditions (e.g., mass flow rate, inlet vapor quality, or geometry effects). Consequently, the sensitivity observed here probably underestimates the true impact of uncertainties in the vapor-liquid separation law on the overall accuracy of refrigerant charge estimation.

In this study, only three components were considered: the accumulator, the filter, and the compressor crankcase. Future work will extend this approach to the heat exchangers. Although the geometries – and thus the internal volumes – of heat exchangers are generally well known, the correlations used to model heat transfer and void fraction introduce significant uncertainty. These correlations can strongly influence the predicted amount of refrigerant stored within the heat exchangers, and may therefore have a substantial impact on the overall accuracy of the refrigerant charge estimation.

Overall, this study addresses only a subset of modeling uncertainties, while real systems may exhibit more complex behaviors. Uncertainties in physical modeling can affect the reliability of charge prediction models trained on synthetic data. Such models should thus be validated across multiple charge levels, and model-generated data should be used with caution and preferably in combination with experimental data.

4. Conclusions

When using a physical model of a heat pump (HP) to train a refrigerant charge prediction model, the accurate representation of all storage volumes is essential. To investigate this requirement, a physical model of an air-to-water HP operating with R32 was developed and experimentally validated. This validated model was treated as an ideal representation of the real system. In parallel, “degraded” models – derived from the reference model but including intentionally mischaracterized components – were created to reflect uncertainties in individual storage volumes.

The charge prediction model, trained on data generated from both the reference and degraded models, was evaluated on a single dataset representative of real-world HP operation. Among the tested components, the suction accumulator proved to be particularly critical for accurately predicting refrigerant quantity, whereas the filter in the liquid line and the compressor shell had a more limited influence. Furthermore, when multiple components are inaccurately characterized, their effects may either partially compensate or amplify one another depending on whether their volumes are under- or overestimated. In the worst case observed here, the relative error in total charge assessment reached approximately 5.5%.

However, for most test cases, the prediction performance remained acceptable, and it is therefore difficult to draw definitive conclusions from this first set of results. Still, the study highlights an important warning: using physical models to generate synthetic data for charge prediction may be more challenging than anticipated, largely due to the difficulty of accurately representing refrigerant distribution in a closed-loop system. The uncertainties examined in this work were chosen based on engineering experience, but real systems may display more complex behaviors. In addition, some key components – such as heat exchangers – were not yet included in the uncertainty analysis and may further affect refrigerant storage.

Overall, this work suggests that while model-generated data may support charge prediction, the approach requires deeper investigation and careful validation. The limitations of physical modeling must be clearly understood before relying on it as a substitute for experimental data.

5. References

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