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Optimal Designed Experiments for Reliable Model Calibration of a fixed-speed Scroll Compressor with R410A and R32

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Abstract. Mainly to provide heat, the building sector accounts for about 18 % of overall global CO2 emissions. By exchanging conventional technologies in the near future, heat pumps are a key technology to systematically decarbonise the heat supply chain. The efficiency of a heat pump strongly depends on its compressor’s efficiency. Thus, the compressor is the subject of current research. The compressor performance depends on the fluid with its inlet and outlet conditions, an appropriate oil, and the mechanic compression principle. Based on that, the performance is expressed by the isentropic and volumetric efficiency. To describe a compressor in detail and fluid independent is challenging. Therefore, many theoretical studies have been conducted, while in comparison experimental studies are rare. To overcome this imbalance, this study focuses a detailed experimental investigation of a 4 kW Copeland scroll compressor with R410A and R32 on a fully automated compressor test stand. Within this paper, we present a method for in-depth uncertainty analysis, which ensures the usability and comparability of our experimental results to other experiments. We store our results in optimal calibrated simulation models based on optimal experimental design. This allows us to reduce experimental effort up to 70 % compared to full factorial experimental designs. To prove the method in a compressor and two fluids, we apply it to a fixed-speed scroll compressor with R410A and R32. The test stand is able to conduct all experiments automatically and part load behaviour of both refrigerants can be summarized in a model according to recent Literature with an overall uncertainty below 8 % for R410A. For R32, the method fails. Utilizing this method, we aim at open-source experiments in order to accelerate the solution of complex research questions.

Keywords: In-depth uncertainty analysis, compressor efficiency, model calibration, fully automated test stand

1. Introduction and State of the Art
Mainly to provide heat for space heating and domestic hot water, the building sector accounts for about 18 % of overall global CO2 emissions [1]. By exchanging conventional technologies in the near future, efficient heat pumps are a key technology to systematically decarbonize the heat supply chain. The efficiency of a heat pump strongly depends on its compressor’s efficiency. Thus, the compressor is the subject of current research [2].
In general, the compressor performance depends on the refrigerant with its inlet and outlet conditions, an appropriate oil, and the mechanic compression principle and commonly the performance is expressed by the isentropic and volumetric efficiency [3]. Conventional refrigerants are hydrofluorocarbons (HFCs) like R134a or R410A, which have a high global warming potential (GWP). In order to reduce the GWP of refrigerants, different directives and legislations restrict the use of refrigerants with a high GWP. Thus, leading for example to the use of dihalogenoalkanes such as R32 with a GWP of 675. Since R410A and R32 differ in thermodynamic properties, their performance in the same compressor might differ as well [4].

To accurately qualify the compressor performance and use the insights for optimal compressor design, there is a need for combined investigations of experiments and modelling. In addition, both the complexity of experiments and the amount of data to be processed increases. Following the metaphor of the audio format MP3, we assume that in the future measurement data will also have to be stored efficiently and accurately in a defined compressed way in order to allow reasonable further processing such as comparison to other test stand results at other institutions or to serve as basis for calibration of further physical models.

In this paper, we therefore propose a method to store raw data efficiently in optimal calibrated models. To ensure the quality and reliability of the data, we do an in-depth uncertainty analysis regarding the measurement data uncertainty, the test stand bias and the calibration process error. Hence, the overall uncertainty of the final calibrated model, which stores the raw data, has three parts: (1) measurement uncertainty of the equipment, (2) bias uncertainties of the test stand and (3) storage uncertainty of the calibration process. Several compressor test stands already exist in the recent literature [5 - 7] as well as modelling approaches [3, 8, 9], which serve an overview of the recent state of the Art for uncertainty quantification and common modeling approaches.

Regarding experiments, Tello Oquendo et al. [5] measure scroll compressors with enhanced vapor injection in a climatic chamber, whereas Cueves and Lebrun [7] focus their work to investigate the impact of rotational speed on compressor efficiency in calorimeters. Yang et al. [10] investigate water-injected process-gas screw compressors to study the effects of rotational speed, injected water mass flow, and discharge pressure on the screw compressor performance. In [11], Zhang et al. study the potential of twin screw compressors for R513A as a R134a replacement. All of the aforementioned experimental studies have test stands according to the standard EN 13771-1 (2017) [5, 7] or give an overview of measurement accuracies of all sensors [10, 11]. However, a detailed in-depth analysis of measurement uncertainty according to GUM considering the test stand bias, was not reported to the best of the authors’ knowledge. In addition, they do not share their measurement data stored in models openly.

With respect to compressor modelling and storage of data, there is a common normative modelling approach according to DIN EN 12900 to model the compressor behavior regarding its input power and its refrigerant mass flow [9]. Besides DIN EN 12900, many different modelling approaches exist in the literature, which differ in black box, gray box and white box models.

In pioneering work, Corberan et al. [12] question the use of different models and polynomial robustness of 10C method according to DIN EN 12900 by analyzing polynomial approaches with less than 10 coefficients. They find that it is not necessary to employ a 10 coefficient polynomial for scroll compressors. For mass flow rate for example, three coefficients are sufficient. However, in order to fit corresponding surfaces, many experiments must be conducted. We therefore propose the optimal experimental design framework to calibrate a model based on the optimal number of experiments. To show the robustness of our method, we compare two common refrigerants (R410A and R32) within the same compressor.

The literature emphasizes, that many theoretical and some experimental studies exist, which show the need for reliable compressor models based on valid experimental data. However, there is a lack of detailed in-depth uncertainty analysis of the presented test stands. In order to make results of different institutions easier comparable and exchangeable, we introduce an extended approach to estimate the uncertainty of measurements. Based on measurement results, we store our results in models that are
calibrated by the optimal number of experiments using optimal experimental design. This yields a calibrated model with uncertainty specifications, which easily can be exchange with others.

We therefore introduce the MoCaVal framework for automated model calibration and validation, which was recently presented by Vering et al. [13] and extend the framework iMoCaVal to a complete bias characterization. In addition, we conduct and evaluate experiments with R410A and R32 to investigate the fluid influence on model calibration and validation.

This publication systematically contributes to an extended characterization of compressor measurement data stored in models and therefore allowing direct comparability between different test stands. The paper is structured as follows:

- Chapter 2 shows the framework iMoCaVal of in-depth uncertainty analysis and optimal experimental design.
- Chapter 3 describes the compressor use case, investigated fluids, and first results obtained by the test stand and an extended bias specification.
- Chapter 4 presents measurement and calibration results for R410A and R32 and contains a discussion afterwards.
- Chapter 5 gives a summary and an outlook based on the obtained results.

2. Optimal Experimental Design applied to Compressors

In a previous paper, Vering et al. presented a framework for automated model calibration and validation (MoCaVal), which was applied to compare conventional calibrated simulation models from the literature to a model that was automatically set up using machine learning [13]. To ensure a slight overview, we present the highlights of MoCaVal in Chapter 2.1 leaving out the machine learning part.

To assess the quality of the measurement data within MoCaVal, an uncertainty quantification was introduced using the Guide to the Expression of Uncertainty in Measurement (GUM) [14].

According to Figure 1, we extend MoCaVal by an extended in-depth uncertainty analysis to iMoCaVal in this paper, which also takes the test stand bias during measurements due to statistical analysis into account (Chapter 2.2). To make our results easily available and exchangeable, we store the data in optimal calibrated models, to the price of calibration uncertainty. We therefore use an optimal experimental design (OED) method to estimate the optimal number of experiments to sufficiently calibrate a compressor model (Chapter 2.3). This method is applied to two refrigerants in a scroll compressor which yields two data models that can be used open-access for usage or comparison.

2.1. Introduction to MoCaVal and its extension to iMoCaVal

According to Figure 1, iMoCaVal is a framework for automated in-depth uncertainty analysis, model calibration and validation for refrigerant compressors up to 30 kW nominal compressor power.

![Diagram](image)

Figure 1: For a specific device under test, iMoCaVal allows the automated model calibration and validation for refrigerant compressors to efficiently and accurately store data and make it reliably shareable.
A detailed description of the test stand, which consists of a vapor compression process without evaporator, is provided in Vering et al. [13] including the accuracy of the measurement equipment.

Within the framework iMoCaVal, we differentiate between three parts: (I) raw data, (II) in-depth uncertainty analysis (III) model output.

(I): From an input point of view, the device under test needs to fulfill the requirements from Table 1 and theory on the subject of model discrimination must be available to exploit the potential of the framework.

(II): Using the test stand and different model formulations, iMoCaVal determines optimal experimental designs and performs necessary experiments. Special focus in this paper is the extension of measurement uncertainty according to GUM by in-depth statistical uncertainty analysis.

(III) As a result, MoCaVal provides calibrated models of the compressor indicating the quality of the model.

Within this paper, we prove the applicability of MoCaVal to different fluids with additional in-depth analysis. We therefore conduct experiments with two different refrigerants from thermodynamic point of view (R410A and R32) with respect to their working envelopes in the same scroll compressor to find the limitations of MoCaVal. To ensure comparability and usability of measurement results, we introduce an in-depth uncertainty analysis. Based on this, we store the measurement data in simulation models from the literature. As it is common, we use the 10C model according to DIN EN 12900 (Eq. 1) and compare it to an advanced model based on similarity theory from Miranda-Mendoza et al. (Eq. 2 and Eq. 3), which was introduced in the literature to model the performance of the halogenated refrigerants R134a, R450A, R1234yf and R1234ze [8, 9]:

$$f(G_i, T_i) = C_1 + C_2 T_e + C_3 T_c + C_4 T_e^2 + C_5 T_e T_c + C_6 T_c^2 + C_7 T_e^3 + C_8 T_e^2 T_c + C_9 T_e T_c^2 + C_{10} T_c^3$$

$$\eta_{is}(\Pi, a_i, n, V_u, T_i, h_i) = \Pi^{a_o} \left( \frac{n^3 V_u}{\Delta h_{ec,is}} \right)^{a_1} \left( \frac{T_e + T_{c,is}}{2} \frac{T_{oda}}{T_{oda}} \right)^{a_2}$$

$$\lambda(\Pi, b_1, \rho_e, p_i, n, V_u) = \Pi^{b_o} \left( \frac{\rho_e}{p_e} \right)^{1.5} n^3 V_u^{b_1}$$

Where \( f(G_i, T_i) \) denotes one function for electrical power \( P_{el} \) and one function for refrigerant mass flow \( \dot{m}_{ref} \). \( \eta_{is} \) is the isentropic efficiency, \( \lambda \) the volumetric efficiency, \( C_i, a_i, b_i \) are calibration parameter, \( T_c (p_e, \rho_e) \) is the temperature (pressure, density) at compressor inlet and \( T_{oda} \) the outdoor air temperature. \( \Pi \) is the pressure ratio that Miranda-Mendoza et al. determined using similarity theory and \( \Delta h_{ec,is} \) the enthalpy difference between isentropic and isentropic outlet state is the compressor volume ratio of Miranda-Mendoza et al. determined using similarity theory and \( \Delta h_{ec,is} \) the enthalpy difference between the inlet state and isentropic outlet state is the compressor outlet temperature (compressor outlet temperature at an isentropic compression). The compressor volume is \( V_u \), the enthalpy difference between inlet state and isentropic outlet state is \( \Delta h_{ec,is} \), \( \Pi \) is the pressure ratio that Miranda-Mendoza et al. determined using similarity theory and \( T_{oda} \) the outdoor air temperature. For the sake of completeness, we denote \( n \) as rotational speed, although it is set constant due to fixed speed compressor investigations.

Obviously, the refrigerators investigated by Miranda-Mendoza to exchange R134a by R450A, R1234yf or R1234ze differ from the refrigerants from this paper (R410A/R32) in terms of molar mass and saturation-pressure characteristics. Nevertheless, we pose the hypothesis that it is possible to cover the behavior of R410A and R32 within the same physical model to at least some extent. To assess the quality of measurement, ensure further usability, and comparability of our results, we conduct an in-depth uncertainty analysis initially, which bases on the following method.
2.2. In-depth uncertainty analysis and test stand bias

Most measurands $Y$ cannot be measured directly. They are determined from other quantities $X_i$.

$$Y = f(X_1, X_2, ..., X_N)$$

For an uncertainty analysis it is therefore necessary to consider uncertainties of all inputs. Type B evaluation of the GUM [14] provides a method to estimate the standard uncertainty $u(x_i)$ of an input quantity $X_i$ based on available information on its possible variability. Those information in general define lower and upper bounds $a_-$ and $a_+$ for $X_i$. If there is no specific knowledge about the contribution of $X_i$ within the interval $a_-$ to $a_+$, one can only assume that it is uniformly distributed. In any case of a distribution more similar to a normal distribution, a rectangular distribution is an estimation to the safe side. The expected value is the midpoint of the interval,

$$x_i = \frac{a_+ + a_-}{2},$$

and its variance is given by

$$u^2(x_i) = \frac{(a_+ - a_-)^2}{12}.$$  

By assuming the interval length to be $2a$ the standard uncertainty can be expressed as

$$u(x_i) = \frac{a}{\sqrt{3}}.$$  

The combined standard uncertainty $u_c(y)$ is based on a first-order Taylor series approximation of Eq. 4. In case that all input quantities are independent, $u_{gum}(y)$ is the positive square root of the combined variance $u_{gum}^2(y)$ given by

$$u_{gum}^2(y) = \sum_{i=1}^{N} \left( \frac{\partial f}{\partial x_i} \right)^2 u^2(x_i)$$

where $f$ is the function given in Eq. 4 and $u(x_i)$ the standard uncertainty evaluated as described above. This method to assess the combined standard uncertainty is used for all target variables.

For a better understanding we show how it is applied to the isentropic efficiency. The isentropic efficiency is calculated from the enthalpies of the different states.

$$\eta_{is} = \frac{h_{2is} - h_1}{h_2 - h_1}$$

The uncertainty of the isentropic efficiency is therefore a function of those enthalpies and its uncertainties. The enthalpies are derived from equations provided by the NIST REFPROP database [15]. The uncertainties given by this database don’t include specific estimates for the enthalpies’ uncertainties. They were thus initially approximated by the percentage uncertainty of the heat capacity in the MoCaVal introduction. Here, the uncertainty estimation is applied to an approximate function to describe the isentropic efficiency which includes only heat capacities and temperatures.

$$\eta_{is} = \frac{c_{p,1\rightarrow2is}(T_{2is} - T_1)}{c_{p,1\rightarrow2}(T_2 - T_1)}$$

In this way the specific uncertainties for heat capacities and temperatures given by the NIST REFPROP database and the manufacturers’ data sheets can be used.

Furthermore, to quantify the repeatability, which means the test stand bias during a measurement of a quasi steady-state operating point, exemplarily two measurement points are selected and measured several times. Based on these detailed measurements, a test stand bias $u_{bias}$ can be recalculated. As introduced, storing the measurement data in a calibrated model for the easy open-access use finally leads to the price of a further uncertainty $u_{storage}$, which needs to be considered as well. We therefore geometrically sum up all parts of uncertainties to ensure an usability and comparability of our measurements:

$$u_{overall}^2 = u_{gum}^2 + u_{bias}^2 + u_{storage}^2$$
2.3. **Optimal Experimental Design for Experimental Effort Reduction**

To calibrate a simulation model accurately, reliable measurement data is necessary. Additionally, to compare data to other measurements or to further exploit the data by external researchers, an in-depth uncertainty analysis allows an universal use of the data. The data is extracted from measurements, which need to be conducted. As experiments are time and resource consuming, they must be carefully planned, executed and evaluated.

In order to fully qualify a compressor in terms of energy, the entire operating envelope must be measured. According to the classical design of experiments, the analysis of the influencing variables results in a full factor plan, which can involve considerable measurement effort. With respect to the models described by Equations 1-3, the number of experiments from the full factorial plan significantly exceeds the number of calibration parameters. To minimize the time and resources required for model calibration, Optimal Experimental Design (OED) allows the number of experiments to be reduced.

In this work, we combine OED with in-depth uncertainty analysis to calibrate a model that accurately predicts compressor behavior and can be reliably used in a variety of applications, especially by external users who may not have the ability to perform experiments. In this context, this procedure might lead to “open-access” experiments, which to our opinion is the future of cooperation in research.

To reduce the experimental effort from the full factorial plan to a minimized number of experiments with OED, it is necessary to define criteria that can evaluate what information content a measurement point has. Such criteria can be chosen when model discrimination has already been completed. This means that the model to be calibrated must already be known in advance. Therefore, the choice of the initial model is crucial for the quality of the final results. In this paper, we choose existing models from the literature according to Equation 1-3 and select the criteria D-optimal OED, which is widely applied in the literature [16].

The variance-covariance matrix serves as basis for the optimization algorithm, which reduces the number of experiments. The variance-covariance matrix is also called Fisher Information Matrix (FIM) and is calculated based on all candidate combinations from the full factor plan. The D-optimal Design maximizes the determinant of the FIM, which determines the model calibration parameter in the best possible way. In contrast, I-optimal Design for example would be applied when the prediction accuracy for the target variable should be optimized. In this context, we want to emphasize that there is a wide range of optimization methods that cannot all be considered here. We use the D-optimal design, which is not necessarily the optimal choice. The choice of the correct optimal design should be investigated in following works.

3. **Optimal Experimental Design applied to Compressors**

Within this contribution, we calibrate models based on measurements for a scroll compressor for the two refrigerants: R410A and R32. Before the calibration can be performed, we want to introduce the two refrigerants and show how the recording of raw data works in a fully automated way.

3.1. **R410A and R32 and their resulting envelopes**

The device under test is the Copeland compressor ZHI18K1P-TFM with 4 kW nominal power and R410A as refrigerant. R410A is a quasi-azeotropic mixture of 50 % R32 and 50 % R125 and has a global warming potential (GWP) of 2088, which is why a phase-out of R410A is necessary in the near future. In contrast, R32 has a GWP of 675.

The thermodynamic behavior of both refrigerants and R134a is summarized in Figure 2 in their corresponding pressure-enthalpy diagrams. While the evaporation enthalpy of R32 is about 20 % higher compared to R410A, the resulting operating envelope of R32 is smaller due to higher compressor outlet temperatures at similar pressure ratios.
Figure 2: Comparison of R410A (light blue), R32 (dark blue) and R134a (red) in a pressure-enthalpy-diagram considering two-phase region and different isothermal curves.

With respect to the models from Equation (2) and (3), which are calibrated in [8] for R134a, we compare the fluid behavior additionally in Figure 2. Obviously, the refrigerants have different thermodynamic behavior, which might complicate the model calibration. That means for our measurements, that the envelope of R32 will be smaller as well as its resulting full factor plan for OED, because of its high compressor outlet temperature even at small pressure ratios. The operation envelopes deduced for the full factor plan are shown in Figure 3 (a) for R410A and Figure 3 (b) for R32.

As introduced in Equation 1-3, the target variables for the model calibration are the electrical power, refrigerant mass flow rate (Eq. 1) and the volumetric (Eq. 2) and isentropic efficiency (Eq. 3). The limits for the operation envelope for the inlet pressure is for R410A $p_{1,\text{min}} = 4$ bar and $p_{1,\text{max}} = 14$ bar. The limits for the compression ratio are 2.5 and 6.5, but since the outlet pressure $p_2$ is also limited between 20 and 44 bar or up to 130 °C compressor outlet temperature according to Table 1, not every combination of $p_1$ and $\pi$ can be measured.

Figure 3: Operation envelope of R410A (a, top) and R32 (b, bottom) as a function of inlet pressure and pressure ratio yielding 36 operating points for R410A and 23 operating points for R32.
In Figure 3a, the R410A candidate set of the full factor plan is shown. Within the limits, 11 factor steps are planned for $p_1$ and 8 factor steps for $\pi$, so that the step size is 1 bar for $p_1$ and 0.5 for $\pi$, respectively. This results in 36 operating points to cover the factor space uniformly.

In Figure 3b, the R32 candidate set of the full factor plan is shown. Within the limits, again 11 factor steps are planned for $p_1$ and due to the vapor pressure characteristics 6 factor steps for $\pi$, so that the step size is 1 bar for $p_1$ and 0.5 for $\pi$, respectively. This results in 23 operating points to cover the factor space uniformly.

3.2. Raw data of R410A and R32 measurements

Within the operational envelope, we can conduct experiments fully automatically for both refrigerants by implementing an experimental design. During a measurement, the test stand controller ensures steady-state conditions by adjusting the inlet temperature and pressure as well as outlet pressure as function of valve positions at the heat sink (water) and in the refrigeration cycle.

To reach a steady-state the inlet temperature and the inlet and outlet pressure are controlled. A measurement point is defined as quasi steady-state if the control variables lay within a certain corridor for a predefined period. The limit for the inlet temperature is ± 1 K. The tolerance for both pressures is ± 2 % absolute.

![Figure 4: Trend of the three control variables inlet temperature and inlet and outlet pressure (normalised) during one entire measurement of an operating point with R410A from start-up to quasi steady-state measurement for about 2000 s.](image)

A measurement of one certain operating point is valid if the quasi steady-state condition is held for 600 seconds. Figure 4 shows an automatic start-up and holding of an operating point for about 2000 s with the evaluated period of 600 s in quasi steady-state. The initial overshoot of the inlet pressure is caused by its dependency on the (strongly increasing) outlet pressure in the given system design. After an operating point was successfully measured, the next operating point is considered automatically.

The Figure shows how the trends of those control parameters look like. As temperature has a valid offset ± 1 K, it is shown on an absolute scale as a function of time. The pressure scale is normalized by their setpoints to show their validity in a corridor of ± 2 % absolute. Since this paper aims at comparing both fluids in the same compressor and calibrating models based on optimal designed measurements, there is no optimization of the test stand control to further speed up measuring individual operating points. This can be part of future investigations.

Figure 4 shows that the test stand is able to conduct experiments fully automatically and hold a set point within quasi steady-state conditions using pre-defined corridors for our target values. In addition, it becomes clear that so far we are not able to set and maintain real steady-state conditions using the control parameter, which will be part of future investigations.

Nevertheless, we will use the results of 600 s quasi steady-state measurements to calculate the mean values and standard deviations for all target values obtained in this period and evaluate it as source of uncertainty (test stand bias) in the already introduced in-depth uncertainty analysis in Chapter 4.1.
Besides temperature and pressure levels during the whole measurements, the test stand records large number of further parameters. Some of them serve to monitor the performance of compressor and test stand. Others are required to evaluate the target variables afterwards. Therefore, Figure 5 shows for completeness two of those parameters – outlet temperature and refrigerant mass flow. An integral overview of the test stand is presented in Vering et al. [13].

Figure 5: Trend of the outlet temperature and refrigerant mass flow during one measurement with R410A within an evaluation period in quasi steady-state conditions.

4. Results

Using the theory of Chapter 2 and the raw data of Chapter 3, we are able to calculate the measurement uncertainty by an in-depth uncertainty analysis in Chapter 4.1. After that, we use the data and the models from Eq. 1-3 to calibrate them according to D-optimal experimental design in Chapter 4.2. Lastly, we discuss our findings in Chapter 4.3

4.1. In-depth uncertainty analysis

Figure 4

According to Equation 11, the overall uncertainty of calibrated models denotes the geometric sum of measurement uncertainty, test stand bias and storage uncertainty due to calibration process. While in a simplified form the measurement uncertainties are already introduced in Vering et al. [13] in Chapter 2.2 the already existing model (Eq. 9) could be extended a detailed model (Eq. 10). It will be applied to measurement data. Therefore, the test stand bias must be qualified. This is done by repeatability tests for different operating points. Within the scope of this paper, the repeatability tests are performed for two measurement points using R410A. These points are located in different areas of the compressor envelope. In addition, one is located on the edge of the envelope whereas the other one lies more in the center. In this way the repeatability should be ensured to be valid for the whole compressor envelope. The selected measurement points are summarized in Table 1. Detailed analysis of further operating points, refrigerants and compressor types are recommended for further studies.

Table 1: Measurement points for repeatability tests. One taken from the edge of the envelope (Point 1), one taken from the centre of the compressor envelope (Point 2).

| Point 1 | Point 2 |
|---------|---------|
| Compression ratio $\pi$ [-] | 5.5 | 3.5 |
| Inlet pressure $p_1$ [bar] | 4 | 11 |

As introduced, the evaluation of quasi steady state operating conditions of each measurement lasts 600 s. With a sample rate of one sample per second this leads to 600 samples for each measurement. For Point 1 three measurements are performed. Point 2 is even measured five times to ensure repeatability over a wider range of measurements. All those measurements are evaluated separately before interpreting them all together using isentropic efficiency as a use case.

The test stand conducted all eight repeatability tests fully automatically and stored the results in result files, which are evaluated in the following. According to Table 3, the deviation during the individual
measurements is comparatively small, especially for the point located near the center of the compressor envelope. For both points the fluctuation lies within less than 3 %. Evaluated for all measurements of the same point the fluctuation is around 5 % in both cases. Table 2 shows the fluctuation ranges and standard deviations for both points analyzed individually as well as combined.

Neglecting measurement uncertainty in the bias quantification, the standard deviations for the isentropic efficiency of all repeatability measurements are plotted in Figure 6. The measurement averages are indicated as three (five) separate operating points in blue in Figure 6a (Figure 6b). Calculating the average of all three (five) operating points for 600 s quasi steady-state conditions yields the overall average in red. Using error bars, we denote the standard deviation of each 600 s quasi steady-state conditions. The standard deviation (std.) is here chosen as a model for the test stand bias, which is very accurate with respect to this 8 measurements. As an estimate to the safe side, we use the higher standard deviation as test stand bias for all measurement points, which now is defined according to Eq. 11 as $u_{bias} = 1.52$.

Table 2: Fluctuation and standard deviations (std.) for individual measurements and evaluated all together for the isentropic efficiency.

|                  | Point 1 | Point 2 |
|------------------|---------|---------|
| Max. fluctuation in measurements | 2.35 %  | 1.85 %  |
| Max std. in measurements          | 0.56 %  | 0.36 %  |
| Fluctuation all measurements      | 5.19 %  | 4.91 %  |
| Max std. all measurements        | 1.52 %  | 1.23 %  |

As introduced, Figure 6 shows the average quasi steady-state operating point with its resulting standard deviation as test stand bias. In addition, we plot the measurement uncertainty according to Eq. 10 indicated by the box around those measurement points. Thus, in this area we trust the measurement data according to GUM method.

It can be seen that the combined uncertainty of the isentropic efficiency is of the same order of magnitude compared to the standard deviations of a single measurement (blue) and smaller than the standard deviation of all series of measurement (red). It amounts to 0.49 % and 0.63 %, respectively. What is remarkable about the combined uncertainties is that they don’t vary within the measurements of one measurement point. They are not sensitive to small variations in the location of a measurement point.

It is apparent, that the uncertainty estimation taking into account heat capacities and temperatures is significantly smaller than the one in [13] using Eq. 9. This shows that the assumption that the uncertainty of the enthalpies is equal to the heat capacities’ uncertainty has a large influence on the combined uncertainty of the isentropic efficiency.

It is therefore of enormous importance to make reasonable estimates and assumptions for the input variables’ uncertainties. Again as an estimate to the safe side, we use the uncertainty model according to Eq. 10 with the worse uncertainty results, which yields the uncertainty of GUM to be: $u_{gum} = 0.63$. 
Figure 6: Standard deviations and uncertainties of the isentropic efficiency determined with Eq. 10 for (a) measurement point 1 and (b) measurement point 2 for R410A.

4.2. OED for test time reduction

Following Eq. 11, we can assess the overall uncertainty of a representative and reliable model, by adding the term $u_{storage}$, which is a result of model calibration process. If we want to fit a model to real measurement data in general, there is a natural deviation between model result and measurement data due to numerical issues or under- and overfitting the data using a model. We therefore measure the difference between measurement data and model result and compute $u_{storage}$ as standard deviation. Giving this information allows external researcher to reliably compare the obtained data stored in our model. Which is a step towards open source experiments.

To calculate $u_{storage}$ the models of Eq. 1-3 must be calibrated to measurement data. To reduce the influence of under and overfitting, we use OED with the D-optimal design to optimally design the experimental plan. Detailed analysis for R410A were already presented in Vering et al. [13], which showed a significant reduction of experimental effort, while simultaneously maintaining a certain degree of accuracy. This approach is extended by R32 in this paper.

Based on the operating envelopes in Figure 3, we show the results of D-optimal design for both refrigerants and the three modelling approaches from Eq. 1-3 in Figure 7. Using the method of full factor plans, measuring R410A needs 36 quasi steady-state operating points. In order to calibrate the models, D-Optimal design reduces number of experiments for C10 to 10 experiments, $\eta_a$ to 3 experiments and $\lambda$ to 2 experiments as absolute minimum. The most of all measurement points lie on the edge of the envelope. It is interesting that an increase in the number of experiments does not necessarily lead to an increase in the variety of measurement points. To reduce the scatter of measurements and thus to increase reliability, points already measured at the edge of the envelope are first approached several times before the D-optimal design proposes further measurement points.

The full factor plan results in 36 measurement points. Applying D-optimal design to the compressor envelope reduces the number of experiments to 10, 3 and 2, just as for R410A. This behavior fits the mathematical expectations. Compared to R410A, however, other operating points and boundary ranges are targeted, which underlines the functionality of the D-optimal design. Using this experimental setups, the test stand can automatically execute all experiments. The obtained measurement results can subsequently be used for calibration to determine $u_{storage}$. The calibration results are shown in the Annex Table A1.
R410A: Compared to the full factor (FFP) plan, which required 51 experiments, Vering et al. reduced experimental effort significantly, while always ensuring the prediction accuracy of the model below 11% at worst, which was about 2% less accurate compared to worst deviation between model and experimental data using FFP.

Finding a reasonable trade-off, they were able to reduce the experimental effort by about 75% to only 12 experiments, which means two experiments above the absolute minimum (10) proposed by OED. Compared to FFP, the models still maintain an average prediction accuracy below 5% for the different modelling approaches, which was at maximum only 1% less accurate than FFP. In order to investigate the fluid dependency of OED for compressor model calibration and hence $u_{\text{storage}}$ for the final assessment, we conduct the same method for the same compressor using R32 measurements in the following.

Table 3: Evaluation of model accuracy for modelling approaches of Eq. 1-3 for R410A and R32. For both refrigerants, there is a comparison of full factor plan to a D-optimal experimental design.

|         | R410A (36) | R410A (10/3) | R32 (23) | R32 (10/3) |
|---------|------------|--------------|----------|------------|
| 10C mean($P_{ch}$ m) | 0.3/0.21   | **0.6/0.33** | 0.08/0.11 | 0.1/0.12   |
| 10C max($P_{ch}$ m)  | 1.82/0.7   | 2.55/1.26    | 0.29/0.44 | 0.51/0.94  |
| $\eta_{is}$ (mean)  | 2.36       | **3.76**     | 30.94    | 34.57      |
| $\eta_{is}$ (max)   | 6.28       | 7.4          | 33.6     | 38.1       |
| $\lambda$ (mean)    | 3.78       | **1.98**     | 1.26     | 5.16       |
| $\lambda$ (max)     | 5.13       | 3.64         | 2.04     | 6.63       |

R32: Compared to the calibration of R410A, which fits the uncertainties of the initial Miranda-Mendoza paper, it is not possible to calibrate the model for isentropic efficiency with sufficient uncertainty, while it is possible to fit the volumetric efficiency sufficiently to measurement data.

These results confirm the understanding that volumetric efficiency is dependent on the pressure ratio, but not so much on the refrigerant. However, modeling of isentropic efficiency is difficult due to the strong refrigerant dependence due to the molar mass, isentropic compression exponent and flow losses that are dependent on the density as well. Thus we confirm our initial hypothesis, that it is possible to model R410A within the Miranda-Mendoza formulation, while it is not possible to model the behavior of R32 sufficiently. Hence, we chose an average storing uncertainty for R410A for the discussion in the next Chapter only.
4.3. Discussion

Using an in-depth uncertainty analysis and applying it rigorously to uncertainty in measurement, test stand bias and calibration uncertainty, we are now able to calculate the final overall uncertainty of final calibrated simulation modes.

According to the GUM notation, we determined as overall uncertainties from Eq. 11 for the models from Eq. 1-3 for

\[
P_{\text{el}}(C_i, T_i, u_i) = f(C_i, T_i) \pm u_{P,\text{overall}} \quad (12a)
\]

\[
\dot{m}_{\text{ref}}(C_i, T_i, u_i) = f(C_i, T_i) \pm u_{\dot{m},\text{overall}} \quad (12b)
\]

\[
\eta_{\text{is}}(\Pi, a_i, n, V_u, T_i, h_i, u_i) = \eta_{\text{is}}(\Pi, a_i, n, V_u, T_i, h_i) \pm u_{\eta,\text{overall}} \quad (13)
\]

\[
\lambda(\Pi, b_i, \rho_i, p_i, n, V_u, u_i) = \lambda(\Pi, b_i, \rho_i, p_i, n, V_u) \pm u_\lambda,\text{overall} \quad (14)
\]

The calculated minimal and maximal overall uncertainties for R410A are summarized in Table 4.

Table 4: Overall minimal and maximal uncertainties for power consumption, refrigerant mass flow rate, isentropic and volumetric efficiency.

|                | Min (abs / %) | Max (abs / %) |
|----------------|---------------|---------------|
| \(P_{\text{el}}\) (W) | 100.97 / 2.05 | 150.98 / 2.74 |
| \(\dot{m}\) (g/s)  | 0.7720 / 1.32 | 1.6237 / 1.72 |
| \(\eta_{\text{is}}\) (-) | 0.0485 / 6.56 | 0.0574 / 7.84 |
| \(\lambda\) (-)    | 0.0303 / 3.66 | 0.0469 / 5.18 |

Within Chapter 4.1 we showed that our test stand is able to conduct experiments fully automatically with a low measurement uncertainty as well as low test stand bias. We also found the control parameter not to be optimized yet, since the target values are not fully formed steady-state, but quasi steady state. In addition, the duration of a quasi steady-state period is not optimized, yet. Both aspects should be considered in further investigations to further decrease the test stand bias.

According to recent findings in the literature [12], we can also state that it is easier to calibrate a model for the electrical power consumption or the refrigerant mass flow than for isentropic or volumetric efficiency, which is indicated by all mean and maximum deviations in Table 3. In addition, model discrimination itself is of high importance to get sufficient prediction accuracy due to model calibration based on experimental data. Nevertheless, Optimal Experimental Design is a promising approach to reduce experimental effort significantly. For further studies, we recommend the investigation of other, more complex compressor types and models such as inverter driven or EVI-setup to prove the robustness of calibration. Finally we should focus further optimal designs or Gaussian Processes to find the best one for reliable compressor model calibration.

Both aspects increase the quality of efficient storage of measurement data, which is absolute requirement for efficient data exchange between different institutions. Efficient storage in calculation models yields an easier and universal comparison to other measurement results and a more universal usage of measurement data by external stakeholder. By increasing complexity of research topics and increasing amounts of data, it is thus our next step towards cooperation in research to conduct experiments in the most open-access way. One promising approach here might be living labs, which even take non-experts into account to conduct experiments. We therefore highly recommend to share as much knowledge as possible to increase quality of research findings in the future and to accelerate research even at increasing complexity.
5. Conclusion

Within this paper, we present a method for efficient compressor model calibration and reliable storage of measurement data using in-depth uncertainty analysis.

The overall uncertainty to store measurement data reliably and efficiently within a model, remains as geometric sum of measurement uncertainties, test stand bias, and uncertainty of calibration. For measurement uncertainty we compared to different approaches and found a more accurate model using isobaric heat capacity and temperatures for uncertainty estimation of enthalpies instead of using uncertainty for enthalpies. The test stand bias was determined by 8 repeatability tests, which indicated a robust reproducibility and the worst test stand bias to be below 2.45%.

Lastly, D-optimal Design of Experiments reduces experimental effort up to 75% (55%) from 36 (23) to 10 (10) experiments for R410A (R32), respectively, while maintaining the uncertainty compared to the full factor plan for both refrigerants. Based on experimental results, we calibrated simplified models from the literature to fully describe the behavior of the power consumption, the refrigerant mass flow, isentropic, and volumetric efficiency. We showed that the average uncertainty due to storage has hardly decreased for 10C (\(\eta_{is}/\lambda\)) from 0.37% to 0.40% for power consumption and from 0.52% to 0.62% for refrigerant mass flow rate (\(\eta_{is}\)) from 3.88% to 4.10% / \(\lambda\) from 1.48% to 1.79%) for R410A, respectively. With respect to R32 we showed that it was not possible to calibrate the model of isentropic efficiency sufficiently. The calibration of 10C and volumetric efficiency leads the same magnitude of deviations as R410A. Within a detailed discussion, we deduce to further improve the quality of data storage by optimization of test stand bias quantification and performing more detailed model discrimination a-priori. In addition, we recommend to investigate the influence of compressor type, model complexity and optimal design method or even Gaussian Processes. All following investigations should aim at what we call open-access experiments, which can be conducted for example in living labs to be able to answer the ever more complex research questions more quickly. This might even include external stakeholders to take part in experiments to allow a further look at the respective subject matter.

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Table A1: Model parameter for Eq. 1-3 after calibration.

|          | R410A          | R32            |
|----------|----------------|----------------|
|          | $P_{el}$ | $\eta_{ref}$ | $P_{el}$ | $\eta_{ref}$ |
| C1       | 24911    | -53.38        | -959.9  | 58.52         |
| C2       | 1146.7   | -4.0002       | -200.9  | 0.4207        |
| C3       | -1268.2  | 8.247         | 270.9   | 0.3734        |
| C4       | 21.29    | -0.08908      | -3.788  | -0.02756      |
| C5       | -43.09   | 0.2625        | 9.183   | 0.08151       |
| C6       | 24.9     | -0.1557       | -5.029  | -0.0103       |
| C7       | 0.1331   | -6.32e-04     | -0.0265 | -5.145e-04    |
| C8       | -0.3991  | 0.0023        | 0.077   | 0.00127       |
| C9       | 0.4022   | -0.00243      | -0.0995 | -9.27e-04     |
| C10      | -0.1456  | 9.34e-04      | 0.0479  | 6.054e-05     |

|          | R410A   | R32            |
|----------|---------|----------------|
|          | $\eta_{ls}$ | $\lambda_v$ | $\eta_{ls}$ | $\lambda_v$ |
| a0       | -0.3209 | -              | 0.08395 | -            |
| a1       | -0.00508 | -            | 0.03521 | -            |
| a2       | -0.0187 | -              | 0.08711 | -            |
| b0       | -       | -0.08337       | -       | -0.08808     |