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"Usability of a virtual sensor in a domestic heat pump application"

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Abstract

As domestic heat pump systems become increasingly important to achieve residential energy efficiency, the need in cost-effective solutions for optimizing system performance is becoming more significant. Digital twin technology is a promising approach to optimize energy efficiency and performance of these systems. Calculated values can be used for control or diagnostic applications. These values can potentially be of better quality than measured data from a simple hardware sensor or even provide data which cannot be measured directly cost-effectively, thus replacing a hardware sensor.
A digital twin of the heat pump was developed and realized as a continuously running simulation model with a focus on utilizing the compressor outlet temperature as a virtual sensor use case. This parameter was selected due to its critical role in achieving optimal control of the heat pump system. The challenge of tailoring the model to individual heat pump systems, which vary from nominal systems due to manufacturing tolerances, is addressed.
The workflow of modeling is presented, emphasizing the balance between representing relevant physical behavior and minimizing computational effort. By optimizing this balance, accurate and efficient real-time data can be provided. Furthermore, the process of tuning the digital twin to each appliance, which may differ from the nominal system, is described. Measurements are used to evaluate the quality of the virtual sensor in comparison to a hardware sensor used in domestic heat pump appliances. The possibility of replacing the hardware sensor with the virtual sensor is discussed.

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Keywords: domestic heat pump; virtual sensor; digital twin; simulation model; calibration

1. Introduction

Domestic heat pump systems are becoming increasingly important to achieve residential energy efficiency [1]. As a result, cost-effective solutions for optimizing system performance are gaining significance. Digital twin technology is a promising approach to optimize energy efficiency and performance of these systems [2]. They are commonly designed to monitor and operate physical assets in real time. On a domestic heat pump, a digital twin can be realized as a continuously running simulation model like shown by Vering et al [3]. Theoretically, it can run on its CPU or in the cloud and can be utilized for multiple use cases. Calculated values within the model can be used for control or diagnostic applications. In some cases, these virtual measurements may offer higher accuracy than conventional hardware sensors or even replace sensors that are costly or impractical to install, thus making it possible to replace them. [4]

This paper investigates the usability of a virtual sensor for the discharge temperature at the compressor outlet based on a digital twin of the heat pump. The chosen variable is critical for efficient heat pump operation. The study addresses key challenges such as tailoring the digital twin to individual appliances, which may deviate from nominal specifications due to manufacturing tolerances and aging effects. Furthermore, it

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explores the trade-off between physical accuracy and computational efficiency, ensuring that the model can run on embedded hardware or in the cloud without compromising stability.

The following sections present the modeling approach, calibration methodology, and experimental validation on the example of an air-to-water heat pump (AWHP) from the appliance manufacturer Vaillant GmbH. Finally, the analysis discusses the potential of replacing hardware sensors with virtual sensors and outlines implications for future applications.

2. Methodology

This section outlines the approach used to design and implement the digital twin, as well as the methodology for integrating measurement data.

2.1. Modeling approach

The digital twin was developed as a continuously running one-dimensional simulation model representing the refrigerant circuit of a domestic heat pump. The modeling strategy prioritizes low computational effort and high numerical stability, enabling deployment on embedded hardware (e.g., appliance CPU) or cloud platforms in a cost-effective manner. Despite its simplified structure, the model is aiming to preserve essential physical behavior and accuracy.

For the sake of simplicity, the modeling approach is to represent only the key components. In case of a domestic heat pump, the key components include the compressor, condenser and expansion valve. To reduce complexity and improve adaptability, the evaporator was excluded from the model. Instead, boundary conditions with real-time sensor data at the inlet of the compressor and outlet of the expansion valve are used (see Figure 1). This hybrid approach allows the digital twin to remain lightweight while maintaining sufficient accuracy for control and diagnostic purposes. Additionally, dynamics of the model were reduced to a minimum. Only components that significantly influence the overall system's dynamic behavior were modeled with time-dependent characteristics. All other components were simplified and represented in a quasi-steady-state manner, therefore neglecting transient effects.

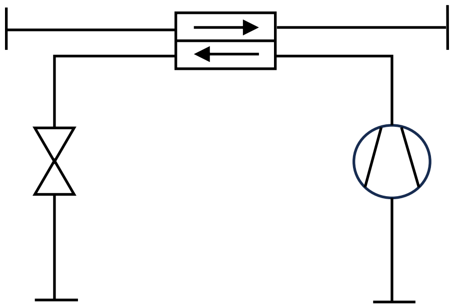

Figure 1. Schematic of domestic heat pump model

The modeling approach was realized in the modeling language of Modelica. This modeling language allows for equation-based descriptions of physical systems, which can be flexibly rearranged and solved depending on the simulation context. [5]

<u>Compressor:</u>

While the test appliance investigated in this study uses a scroll compressor, the modeling approach is designed to be independent to the specific compressor type, ensuring a broad applicability. Given the relatively high dynamic behavior of compressors compared to other components in the refrigerant circuit, dynamic effects were deliberately neglected to reduce computational complexity. Instead, a quasi-steady-state model was implemented, which sufficiently captures the essential thermodynamic behavior of a compressor while maintaining computational efficiency. The compressor model is based on three key efficiency parameters: the isentropic efficiency η_{is}, volumetric efficiency η_{vol} and the mechanical efficiency η_{mech}. The **isentropic efficiency** η_{is} is defined as the ratio of isentropic power P_{is} and the electric Power P_{el}:

$$\eta_{\mathrm{is}} = \frac{P_{\mathrm{is}}}{P_{\mathrm{el}}} \tag{1}$$

The electric power P_{el} is the actual power needed to run the electric-driven compressor. In the case of this domestic heat pump appliance, the compressor is driven by a motor in combination with an electric inverter. The isentropic power represents the theoretical power required for an ideal isentropic compression process. It is calculated based on the refrigerant mass flow rate $\dot{m}_{\mathrm{ref}}$ and the enthalpy difference between the isentropic outlet $h_{\mathrm{comp,out,is}}$ and the actual inlet state $h_{\mathrm{comp,in}}$:

$$P_{\mathrm{is}} = \dot{m}_{\mathrm{ref}} \left(h_{\mathrm{comp,out,is}}(p_{\mathrm{cond}}, s_{\mathrm{comp,in}}) - h_{\mathrm{comp,in}}(p_{\mathrm{evap}}, T_{\mathrm{comp,in}}) \right) \quad (2)$$

Here, $h_{\mathrm{comp,in}}$ can be derived from the evaporation pressure p_{evap} and the compressor inlet temperature $T_{\mathrm{comp,in}}$. The isentropic outlet enthalpy $h_{\mathrm{comp,out,is}}$ is obtained assuming ideal compression with constant entropy, using the condensation pressure p_{cond} and the inlet entropy $s_{\mathrm{comp,in}}$ as parameters. To model this effectively with available data, a fit was done based on the pressure ratio pr between condensation and evaporation pressure. The equation used to calculate the isentropic efficiency η_{is} is of the form:

$$\eta_{\mathrm{is}} = \frac{C_0}{K_1 - K_2} \left(e^{-K_2\,(pr - X_0)} - e^{-K_1\,(pr - X_0)} \right) \quad (3)$$

With help of the parameters C_0, K_1, K_2 and X_0 the isentropic efficiency can be fitted according to available data. The mechanical efficiency η_{mech} accounts for mechanical losses within the compressor, such as friction in bearings or leakages. It is defined as the ratio between isentropic power P_{is} and the shaft power P_{shaft} delivered by the motor to the compressor mechanism:

$$\eta_{\mathrm{mech}} = \frac{P_{\mathrm{is}}}{P_{\mathrm{shaft}}} \quad (4)$$

Determining the mechanical efficiency of the compressor typically requires internal measurements that are not feasible with standard domestic heat pump appliances. To circumvent this limitation, the mechanical and isentropic efficiencies are combined into a single effective parameter:

$$\eta_{\mathrm{is,eff}} = \eta_{\mathrm{mech}} \cdot \eta_{\mathrm{is}} \quad (5)$$

The **volumetric efficiency** η_{vol}, which defines the mass flow rate of the refrigerant in the compressor model, can be computed as a function of the refrigerants volume flow $\dot{V}_{\mathrm{ref}}$ and the compressor speed n_{comp} multiplied by the constant V_{disp}, which represents the displaced volume per revolution:

$$\eta_{\mathrm{vol}} = \frac{\dot{V}_{\mathrm{ref}}}{n_{\mathrm{comp}} \cdot V_{\mathrm{disp}}} \quad (6)$$

The displaced volume per revolution is defined by the compressor model and is considered a constant. To use the digital twin as a basis for a virtual sensor, the refrigerants state is calculated at all points of the refrigerant circuit. A possible use case for a virtual sensor is e.g. the discharge temperature T_{disch} at the outlet of the compressor. It can be calculated with the help of the isentropic efficiency η_{is} defined in equation $\eta\mathrm{is} = \frac{P_{\mathrm{is}}}{P_{\mathrm{el}}}$ (*1*). Using that equation and a variation of equation $P\mathrm{is} = \dot{m}_{\mathrm{ref}} \left(h_{\mathrm{comp,out,is}}(p_{\mathrm{cond}}, s_{\mathrm{comp,in}}) - h_{\mathrm{comp,in}}(p_{\mathrm{evap}}, T_{\mathrm{comp,in}}) \right)$ (*2*), the discharge temperature T_{disch} is derived from the discharge enthalpy h_{disch} at the outlet of the compressor and the condensation pressure p_{cond}:

$$T_{\mathrm{disch}} = T(h_{\mathrm{disch}}, p_{\mathrm{cond}}) \ \text{ with } \ h_{\mathrm{disch}} = h_{\mathrm{comp,in}} + \frac{h_{\mathrm{comp.out,is}} - h_{\mathrm{comp,in}}}{\eta_{\mathrm{is}}} \quad (7)$$

Condenser:

The condenser transfers heat from the refrigerant to the heat transfer fluid, in the case of an AWHP, water. A plate heat exchanger is commonly used for this purpose, where both fluids flow through separate compartments divided by a metal sheet. To ensure numerical stability and physical accuracy in the digital twin, the condenser is modeled using a finite-volume approach. Each finite volume, commonly referred to as a cell, includes an energy balance to capture the spatial distribution of refrigerant and its thermal interaction with the water circuit. This discretization is essential for representing the dynamic behaviour of the condenser, which is assumed to be the main source of inertia in the refrigerant circuit. The heat flow in each cell $\dot{Q}_i$ is calculated by equation $\dot{Q}_i = kA \cdot \Delta T_{\log,i} \approx kA \cdot \Delta T_i$ (8) using a parameterized heat transfer coefficient multiplied by the effective heat transfer area and summarized as a single effective parameter kA and the logarithmic temperature difference $\Delta T_{\log,i}$ between the fluids. Latter simplifies to a normal, local temperature difference ΔT_i for a discretized model. The simplification is justified by the assumption of locally constant temperature gradients within each cell.

$$\dot{Q}_i = kA \cdot \Delta T_{\log,i} \approx kA \cdot \Delta T_i \tag{8}$$

Additionally, pressure loss inside of the condenser is being neglected and thus the inlet and outlet pressure of the condenser are equal.

Expansion Valve:

In most domestic heat pumps, the expansion process is controlled by an electronic expansion valve (EEV) [6]. This component consists of a motor-driven needle mechanism, where a stepper motor precisely adjusts the axial position of a conical needle. By doing so, it regulates the effective flow area $A_{\text{eff,EEV}}$ of the orifice. The step count of the stepper motor is commonly being used to control the position of the needle. This mechanical design ensures minimal leakage and enables fast response times, making the EEV well-suited for dynamic control of the refrigerant circuit. Due to its rapid actuation and the fast thermodynamic changes it induces, the EEV is modeled in quasi-steady-state. Similar to the modelling approach of the compressor, this method balances physical accuracy with computational efficiency. The effective flow area $A_{\text{eff,EEV}}$ is determined via a lookup table based on the step count of the motor. If the refrigerant mass flow rate $\dot{m}_{\text{ref}}$ is of interest, it can be calculated with the help of the Bernoulli equation as a function of the effective flow area $A_{\text{eff,EEV}}$, the refrigerants' density $\rho_{\text{in,EEV}}$ and the condensation p_{cond} and evaporation pressure p_{evap}. Despite its assumptions of incompressible and single-phase flow, it has proven effective for modeling EEV behaviour in similar contexts [7]:

$$\dot{m}_{\text{ref}} = A_{\text{eff,EEV}} \cdot \sqrt{2 \cdot \rho_{\text{in,EEV}} \cdot (p_{\text{in,EEV}} - p_{\text{out,EEV}})} \tag{9}$$

2.2. Online Calibration

To ensure the digital twin accurately reflects the behavior of the specific appliance from the customer, including manufacturer tolerances and aging effects, a special developed methodology is introduced. This method is referred to as "online calibration" (OC) and enables the adaptation of the simulation model to real-world data from the appliance in operation. The OC is structured into two phases: The initial calibration and the continuous calibration. The **initial calibration** establishes a reliable baseline by aligning the digital twin with the nominal characteristics of the specific appliance. This step ensures that the model starts from the best available state possible and provides reliable outputs from the first beginning of operation. Optionally, this initial calibration can be carried out several times in the lifetime of the appliance, e.g. because of re-initialization of the appliance. On the other hand, the **continuous calibration** is carried out on a regular basis. It refines the digital twin progressively using live data of the specific appliance. This phase allows the digital twin to adapt to appliance-specific deviations and evolving conditions over time. It ensures that the model remains accurate despite changes due to wear, environmental influences, or long-term drift in sensor behaviour. Both phases are described in detail in the following sections.

Initial calibration:

To establish a reliable starting point for the digital twin, a dedicated initial calibration routine was developed. A central element of this routine is a reference drive procedure for calibrating the EEV. While the "closed" position of the EEV is specified by the manufacturer, it introduces a significant tolerance that can affect the accuracy of the digital twin if the step count is used directly as an input parameter. The reference drive aims to identify the actual closing point of the EEV, therefore reducing the uncertainty introduced by manufacturing tolerances to a minimum. Additionally, a continuous drive of this uncertainty over time is observed. This can be explained due to its mechanical design and can be described as an aging effect of the component. The conical tip moves into its seat which causes the position to change over time thus changing the value of the "closed"-position. To take this effect into account, a repetition of the procedure on a regular basis is planned. This step is identified to be essential for ensuring that the effective flow area $A_{\text{eff,EEV}}$, derived from a lookup table depending on the current step count, corresponds accurately to the physical state of the valve.

Next to the described process for an initial calibration of the EEV, sensor data are also part of the process of initial calibration. While sensor data must be within certain pre-defined tolerances, the highest accuracy possible is still desired. In the case of crucial sensor data, which heavily influences the accuracy of the digital twin, such as condensation and evaporation pressure, an initial calibration is additionally proposed. Both pressure data are typically measured with the help of pressure sensors located at the in- and outlet of the compressor. At certain points in the initial calibration process, e.g. when the heat pump is in a standby phase, the condensation and evaporation pressure should be equal. If an offset can be still observed, this value is saved for upcoming operation points. This offset is taken as an offset in upcoming operation of the appliance, where both pressure levels are being used in a calculation, thus achieving a higher accuracy.

Continuous calibration:

Contrary to the initial calibration, this part of the calibration is required in regular steps throughout the entire lifetime of the appliance. Due to component and system tolerances, and their shifts throughout the lifetime, continuous calibration forms the essential basis for maintaining model accuracy. The concept is to manipulate defined key parameters of the digital twin through a pre-defined interface and follow a procedure similar to parameter fitting in conventional physical models. Data used for this part of the OC is acquired under steady-state conditions only, where the system variables remain nearly constant over time. After positive detection of steady-state condition, additional system variables are calculated which are needed for the further process. A dedicated function was implemented for detecting the steady-state condition and saving relevant system variables. This function is observing several key variables constantly over time, while they must stay within a certain respective tolerance. Key variables and their tolerances are pre-defined and can e.g. be state variables like condensation pressure, compressor inlet temperature or outlet temperature of the condenser. To define the tolerances and get a picture of the possible signal noise, measurements have been done over the whole measurement chain, including the electrical connection and other electrical components needed for capturing the signal. Additionally, appliance lab data have been used for the definition of the tolerances. With that, the function aims to identify time periods where the signal stays within a certain period. A time t_0 is defined at the start of that period and gets overwritten, as soon as one of the observed system variables is out of its respective tolerance. Only after a passed period without reset, a follow-up procedure is triggered, which calculates the averages of all relevant system variables, beginning from t_0, and saves this as one steady-state operation point. A steady-state detection is exemplary shown in Figure 2, where time is plotted on the x-axis and an example system variable on the y-axis. The dotted boxes represent the period where steady-state is currently investigated, with the height of the box representing the tolerances.

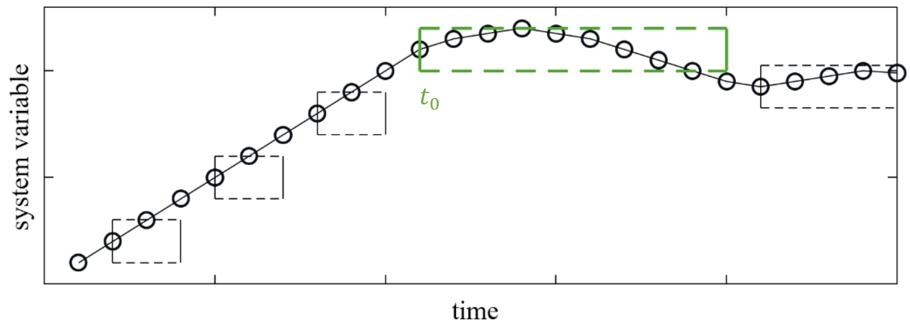

Figure 2: Exemplary schematic of steady-state detection

Once a steady-state operating point is identified, it is first validated by comparison to already existing points. Multiple system variables are used for the comparison, most importantly the variables responsible for defining the value for the virtual sensor. It is considered valid if the Root-Mean-Square-Error (RMSE) is lower than a defined threshold. The RMSE is defined as:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{n}} \tag{10}$$

Once an operating point has passed that criterium, it is saved on the appliance and added to the online data. After enough new data points have been collected, an OC is triggered. The number of new data points is defined by a threshold and is carefully selected to minimize computational effort and possibly reducing numerical instability. These instabilities caused by abrupt parameter changes are expected. To further mitigate numerical issues after recalibration, PT1 filters are applied to smooth the impact of parameter changes. The whole workflow is schematically outlined in Figure 3.

For the example of a virtual sensor of the discharge temperature at the outlet of the compressor, a key variable to calculate the discharge temperature is the isentropic efficiency η_{is} of the compressor and can be calculated according to equation $\eta\mathrm{is}= \frac{P_{\mathrm{is}}}{P_{\mathrm{el}}}$ (*1*). Data needed for that calculation are obtained from tests of different variety and are all obtained under steady-state condition. For the calibration they can be categorized in three categories, ranked by importance:

- Manufacturer data: This data is obtained by the component manufacturer, unlike the other two categories which are obtained by the appliance manufacturer. It is part of the components specification and was obtained under various operating conditions.
- Laboratory data: Measured by the appliance manufacturer under identical refrigerant and hydraulic configurations as the target appliance, the data of this category was obtained by several example appliances. The number of different appliances tested typically ranges from two to five and is not considering any major aging effects.
- Online data: Collected from the specific appliance in the field the digital twin is depicting, it is possible to capture tolerances and aging effects specific to that unit.

All

The process of calibration itself was designed to use as little computational effort as possible. The equation of the entity to be calculated must be provided explicitly. For the example of a virtual sensor of the discharge temperature, equation $\eta\mathrm{is}= \frac{C_0}{K_1-K_2}\left(e^{-K_2\,(pr-X_0)} - e^{-K_1\,(pr-X_0)}\right)$ (*3*) is used. In the calibration process, the parameter of the equation is adapted to the gathered data. This is done by solving a nonlinear least-squares optimization problem, where the goal is to minimize the sum of squared differences between the model output and the measured data:

$$\min_x \sum_{i=1}^{n} [f(\boldsymbol{\theta}, x_i) - y_i]^2 \qquad (11)$$

The optimization algorithm iteratively searches for the parameter set $\boldsymbol{\theta}$ that result in the best fit between the model output $\mathrm{f}(\boldsymbol{\theta}, \mathrm{x_i})$ and the gathered data y_i, ensuring that the virtual sensor reflects the actual system behavior as accurately as possible.

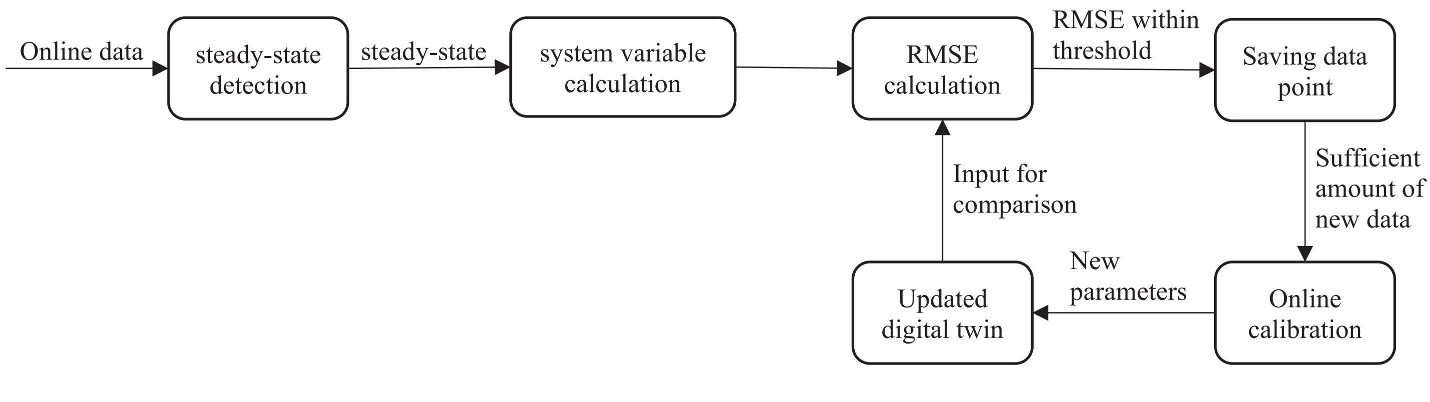

Figure 3. Workflow of OC.

The digital twin was conceptualized and modeled according to the proposed method. The described method was developed in a model-based approach with the help of a physical simulation model. Finally, the method was exemplary tested based on data of a real heat pump appliance, including its full software.

3. Discussion

After describing the approach and implementation for keeping the digital twin's accuracy throughout the appliance lifetime, this section will present the results and discuss its effectiveness. The described method was carried out as an example based on data from one appliance for a total of three months. As a use case for a virtual sensor, the discharge temperature T_{disch} was selected. On the one hand this sensor data is used for controlling the appliance for certain functions. On the other hand, this data is crucial for ensuring that the refrigerant circuit operates within its specified limits. These limits are specified beforehand by the compressor manufacturer and are strict as they serve to protect the compressor from damage. Therefore, the appliance manufacturer must be careful in the design of its software to always keep this limit and additionally needs a reliable sensor. To use the virtual sensor as a replacement for the hardware sensor, accuracy and reliability is in focus.

Offline data from the compressor manufacturer and from the appliance manufacturer of the example appliance are used. In Figure 4 the isentropic efficiency $\eta_{\mathrm{is,eff}}$, relevant for calculation of the virtual sensor, is plotted over the pressure ratio pr between condensation and evaporation pressure. While the compressor manufacturer data allows for a good baseline (dotted line), the appliance manufacturers data further refines the fit to the actual real-life appliance (solid line).

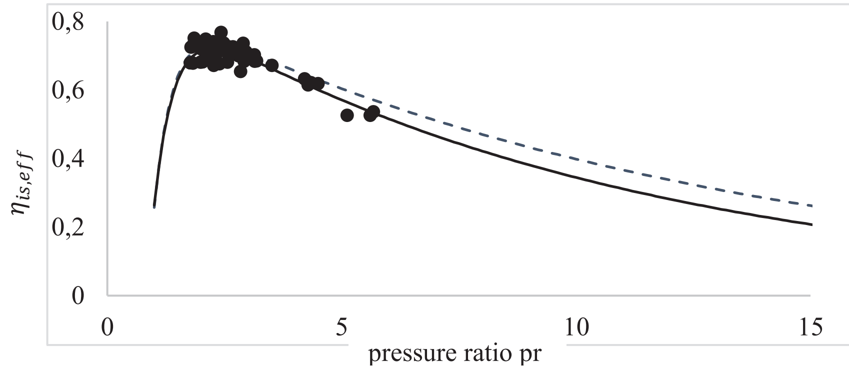

Figure 4: Isentropic efficiency for different segments of compressor speed

To show the working principle of the described OC and discuss its effectiveness, different iterations of the OC are shown in Figure 5. These iterations represent the ones done in the investigated three months period. The isentropic efficiency of the compressor η_{is} over the pressure ratio pr is plotted. The line represents the calculation by the digital twin of each iteration while the points used for the calibration are plotted alongside. Offline data are shown in circles and remain the same over all iterations as they are obtained beforehand and therefore not changed. The online data are visualized as crosses and are different over all iterations, as data points get replaced by new data according to the FIFO method. While from the initial beginning the fit follows the points from the offline data good, with each iteration it shifts towards the online data, as intended. It becomes clear that the weights defined for the OC are crucial for achieving a good calibration to represent the real-life appliance. The weights are heavily depending on the ratio of available offline and online data. Adding no weights, and thus having the same importance of each data, a shift to online data would be much harder to achieve and would require a higher number of online data points. Because the online data points acquirable are limited, the weight factors must be carefully defined.

Noticeably, the online data covers a smaller range of the pressure ratio than the offline obtained data. During normal operation mode in the heating period, the heat pump typically doesn't go into envelope corners, thus producing data only in a limited area of the envelope. Very low- or high-pressure ratios stay untouched in normal operations. Despite of this fact, the appliance still needs to reach these corners, e.g. when a high heat demand is needed. During this time, the digital twin must be able to reflect the appliance correctly as well. Due to the method of the presented OC, this is given with taken offline data into account and emphasized the need for a physical model in combination with a high variety of fitting data.

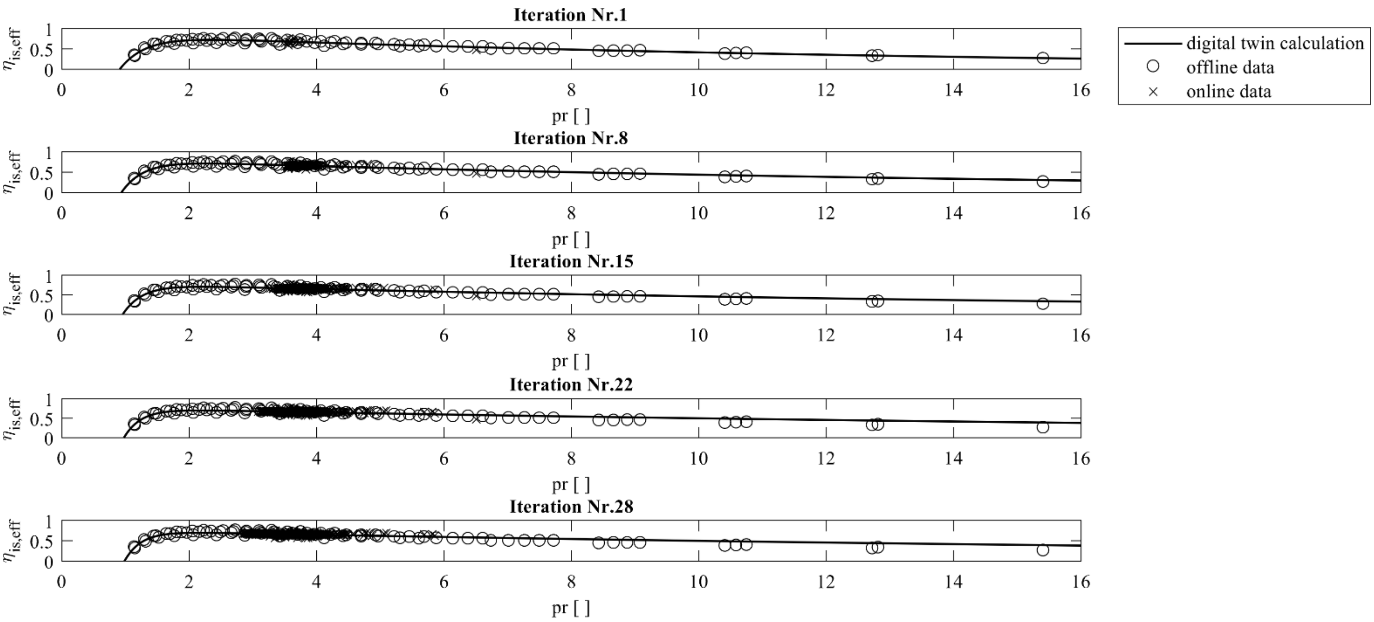

Figure 5. Different iterations of calculating compressor isentropic efficiency after OC

For the use case of using the digital twin as a basis for a virtual sensor, the isentropic efficiency is of great importance. With getting the isentropic efficiency more accurate due to the online calibration, it is expected that also the virtual sensor is getting more accurate, compared to the real temperature of the refrigerant. The influence of the isentropic efficiency on the discharge temperature T_{disch} is seen through equation $T\text{disch}= T(h_{\text{disch}}, p_{\text{cond}})$ with $h_{\text{disch}} = h_{\text{comp,in}} + \frac{h_{\text{comp.out,is}} - h_{\text{comp,in}}}{\eta_{\text{is}}}$ (*7*). The influence of the calibration on the discharge temperature is shown in Figure 6. Specifically, it shows the difference between the discharge temperature predicted by the virtual sensor and the value measured by the physical clip-on sensor over time. Vertical lines are drawn when an OC has been carried out. The plot highlights how calibration reduces the deviation, thereby improving the reliability of the virtual sensor with each OC. Noticeably, deviations still occur even after several calibrations, due to different operating conditions.

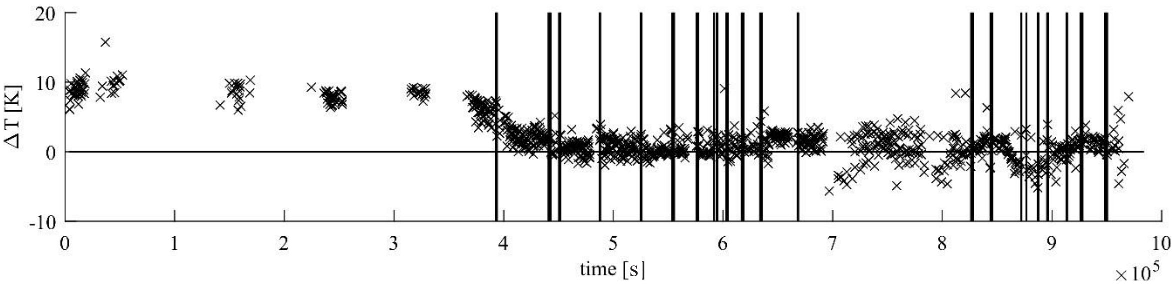

Figure 6: Influence of OC on discharge temperature

One of the main arguments for using this as a virtual sensor use case is that there are only limited ways to measure the discharge temperature effectively. Probably the most cost-effective way is to install a temperature sensor on the outer side of the pipe wall. This can be done without a major impact to the refrigerant circuit and is easily replaced if necessary. Such a clip-on sensor effectively measures the outer wall temperature of the pipe and is also influenced by the temperature of the ambient. The virtual sensor is promising to better represent the discharge temperature through the described calibration method, thus allowing the heat pump to use this entity for control or diagnostic purposes. Noticeably, the virtual sensor improves in its accuracy, underlining the importance of a certain amount of online data and calibration. While it is crucial to gather this online data to achieve high accuracy, it becomes clear that without them the accuracy is worse, thus diminishing the accuracy in the first phases of the appliances' lifetime. With a worse accuracy at the beginning of the lifetime, a replacement of the hardware sensor is not possible, as the importance of that value is equal at the beginning as further in the appliance lifetime. A possible solution would be to include a part of the continuous calibration in the initial calibration, while an external sensor for measuring the discharge temperature during this process would be necessary. Other options would include the possibility to calculate the discharge temperature through other measurable entities. These must be carefully chosen and undergo the OC to accurately represent the discharge temperature.

4. Conclusion and Outlook

A modelling approach and online calibration for a digital twin was presented. The digital twin represents a domestic heat pump and can be used as a basis for a virtual sensor. The modeling process was done with a strong focus of minimizing computational effort while still maintaining thermodynamic accuracy. The online calibration method is divided into two parts: initial calibration and continuous calibration. While the purpose of the initial calibration is to create the best possible baseline to have a reliable digital twin, and thus a reliable virtual sensor from the start, the continuous calibration collects data from the specific appliance continuously. The collected data is gathered and used together with other data, to calibrate the digital twin on a regular basis. This method ensures the accuracy of the digital twin and thus the virtual sensor over lifetime, including manufacturer tolerances and aging effects.

Results are presented and discussed, where a positive effect of the continuous calibration is clearly visible. The accuracy of the discharge temperature at the outlet of the compressor is improved over the lifetime, thus enabling the usability of a virtual sensor based on the digital twin. It is noted that the accuracy of the virtual sensor improves during the investigated time, thus making it difficult to use the virtual sensor at the start of the lifetime.

To further evaluate the accuracy of the virtual sensor, a special test bench is to be used. Much more accurate and reliable in-fluid sensors and sensors for measuring further data, e.g. refrigerant mass flow rates, are used instead of the sensors of a series domestic appliance.

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